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Book review

Nonlinear identification and control—a neural network approach

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The rich materials on modeling and control using linear system theory do not mean that the world is linear rather than nonlinear, but actually reflect our awkward situation of having too few mathematical tools available to deal with the complex nonlinear systems in reality. In many cases, the representation of signals and descriptions of systems are not necessarily the best but sacrificed for the convenience of mathematics. As the systems become ever complex, the drawbacks of linear system description become prominent such as its "local" applicability. Thanks to the collective efforts of many researchers, many significant and fundamental contributions have been made in neural network (NN) control and identification (Ge, Hang, Lee, & Zhang, 2002; Ge, Lee, & Harris, 1998; Lemmon & Michel, 1999; Lewis, Jagannathan, & Yesildirek, 1999; Lewis & Parisini, 1998; Narendra & Lewis, 2001; Narendra & Parthasarathy, 1990) and among others. While the works before earlier 1990s were more of empirical, emphasis has been on system identification and control system design using neural network with rigorous mathematical treatments, and detailed analysis of stability, robustness and convergence of the closed-loop systems (Ge et al., 1998, 2002; Lemmon & Michel, 1999; Lewis et al., 1999; Lewis & Parisini, 1998; Narendra & Lewis, 2001; Narendra & Parthasarathy, 1990). Neural network offers a powerful tool in modeling and control of nonlinear systems over a compact set rather than a small neighborhood around the origin of the linear system approximation.

The book under review is developed under the same spirit technically, and gives an excellent introduction to, and systematic development of system modeling and control using neural network. It covers three main aspects of nonlinear identification and control using neural networks: (i) fundamental principles of neural networks, (ii) nonlinear identification using neural networks, and (iii) nonlinear control using neural networks. Simulation and experimental tests were used to demonstrate the operation and effectiveness of the methods and techniques developed in the book. The contents reflect the most research achievements of the author and his co-workers in the area over the years, with each chapter stay fairly independent of the others. The book is well organized and well written. The concepts and ideas are clearly presented with mathematics, illustrations, simulation or experimentation. For anyone interested in neural network identification and control, this book should serve as a good introduction and valuable reference.

The book consists of nine chapters organized in three distinct parts as follows. In the first part, i.e., Chapter 1, after a brief overview of neural networks and their architectures, the author introduced various types of neural networks including radial basis function (RBF) networks, Gaussian RBF (GRBF) networks, polynomial basis function networks, fuzzy neural networks, and wavelet networks, and their function approximation properties. Then, a few widely used learning algorithms were given including the error back-propagation learning algorithm, the sequential learning algorithm, and the least-mean-squares algorithm. Readers may refer to (Ge et al., 2002) for more complementary algorithms for learning and adaptation. Finally, applications of neural networks were briefly discussed, which include classification, filtering, modeling, prediction, control and hardware implementation.

In the second part, the author presented four nonlinear identification methods using neural networks as detailed in Chapters 2–5, respectively. They are (i) sequential nonlinear identification, (ii) recursive nonlinear identification, (iii) multi-objective nonlinear identification, and (iv) wavelet based nonlinear identification. System identification consists of two portions: the selection of an appropriate identification model and the choice of a tuning algorithm to find the parameters for the output of the model to best match that of the real system for the same inputs. System identification using neural networks has received much attention in recent years as neural networks offer a powerful tool in approximating complex and nonlinear dynamic systems. The distinct features of individual chapter are described as follows.

Chapter 2 presented the sequential identification method for nonlinear dynamic systems based on variable neural networks in continuous time. While choosing a prefixed NN structure for system identification is common, it may lead to an NN model that is either too large or too small for the system. In the literature, two approaches have been used to solve the problem: to prune a large network or to increase a small network until the optimal network complexity is found. In this book, a new network structure, a variable GRBF neural network was detailed using the nice approximation properties of GRBF network in interpolation and localization, where the size of the network can be either increased or decreased accordingly as needed fairly easily. Dynamic system modeling using neural networks was then presented, followed by stable neural network identification proven by

Lyapunov analysis. For real-time applications, observations are made on-line or sequential. Sequential nonlinear identification was then presented for single-input and single-state (SISS) and multi-inputs and multi-states (MIMS) nonlinear systems using variable neural networks. Stability and convergence of the overall identification scheme is guaranteed through Lyapunov synthesis.

In Chapter 3, recursive nonlinear identification was presented for nonlinear systems described fundamentally by Nonlinear Auto-regressive Moving Average (NARMA) models in discrete-time using input and output data. For convenience of discussion, Volterra polynomial basis function (VPBF) network was used for function approximation. The proposed method basically consists of three steps using (modified recursive) least-squares methods (LSM):

(i) Off-line structure selection using orthogonal LSM to obtain an NN of an appropriate size with the selected set of Volterra polynomials arranged in the order of importance for function approximation.
(ii) On-line structure selection using orthogonal LSM to augment the network for appropriate complexity such that the network can approximate the system to be identified sufficiently for changing dynamics.
(iii) Recursive Learning using modified recursive LSM for parameter update for the NN model to match the characteristics of the nonlinear systems.

For nonlinear system identification, while different objectives or performance indices can be used, they are often conflicting and no identification can be considered best with respect to all objectives. The problem of multi-objective nonlinear identification was studied in Chapter 4 for systems described by the NARMA model with exogenous inputs (NARMAX) with the following three performance indices (or cost functions) considered as the objectives: the Euclidean distance and the maximum of measurement difference between the real system and the nonlinear model, and the complexity measurement of the nonlinear model. VPBF and GRBF networks are used to represent the nonlinear systems. After a brief discussion of the Genetic Algorithm (GA) and the problem of model selection, a multi-objective identification algorithm was presented based on the method of inequalities and the genetic algorithm.

Chapter 5 is dedicated to nonlinear identification for nonlinear dynamic systems using wavelet decomposition as it provides a useful basis for localized function approximation with any degree of regularity at different scales and with any accuracy. The chapter started with the introduction of orthonormal wavelet bases, wavelet series representations and wavelet networks, then the author presented the identification methods using fixed wavelet networks and variable wavelet networks, and finally introduced the identification method using B-spline wavelet for possible different applications where it not essential for the wavelet to be orthonormal.

In the third part, the book is dedicated to NN control system design for three different types of nonlinear systems as detailed in Chapters 6–8, and nonlinear neural control application for combustion processes in Chapter 9. For control system design using neural networks, two problems need to be considered: (i) the selection of a particular control structure, and (ii) the actual adaptive or tuning algorithms for achieving closed-loop stability.

In Chapter 6, nonlinear adaptive neural control was for a class of affine nonlinear systems in continuous time based on GRBF neural networks under the assumption of full state measurements. In contrast to common adaptive neural control schemes with a fixed neural structure, the developed neural controller uses variable neural networks to solve the possible problem of using either over- or under-sized neural networks. The control scheme ensures the stability of the closed-loop system in the presence of modeling error. The tracking errors converge to the required accuracy through the adaptive control algorithm derived by combining the variable neural network approximation and Lyapunov synthesis techniques.

In practice, only the inputs and outputs rather than full states are measurable for many industrial systems. In addition, time delay may exist. Predictive control based on a linear model has been widely used in industry. However, industrial processes usually contain complex nonlinearities and linear models are not acceptable when the system is operating away from the equilibrium point. In Chapter 7, nonlinear predictive control was investigated using NN as a nonlinear approximation tool for affine nonlinear systems in discrete time. The developed predictive neural controller is relatively simple and easy to implement using the affine nonlinear predictors as there is no need to solve a nonlinear programming problem for the optimal control if no additional constraint is imposed on. By modifying the recursive LSM, an on-line weight learning algorithm for the neural networks was developed for the affine nonlinear predictor.

In Chapter 8, robust variable neural predictive control was presented for a class of discrete-time affine unknown nonlinear systems by combining variable structure control with sliding mode and nonlinear neural predictor for output prediction. After the concept of variable structure control was introduced for linear systems, variable structural neural predictive control was presented by (i) minimizing the prediction error and (ii) using neural networks to approximate the unknown nonlinear functions. The idea was further extended to generalized predictive control by minimizing both the prediction error and control inputs. The proposed control schemes provide good stability and robustness for the nonlinear systems. Based on the recursive LSM, a recursive learning algorithm is given for stable weight update.

Finally, the control part was closed by the case study of nonlinear neural control in Chapter 9 for active stabilization of combustion processes that are characterized by several interacting physical phenomena and a wide variety of dynamical behaviors. The chapter started with the dynamics of the system, went through the discussion of NN-based mode observer, and stopped at the output predictor and control. The effectiveness of the nonlinear neural control was firstly demonstrated through simulation of an unstable combustor with six modes and then by an experimental combustion test rig with a commercial combustor.

In summary, this book provides an excellent structured presentation of modern nonlinear identification and control methods and techniques. It is a valuable introductory book for the newcomer to the field of nonlinear identification and control and the practicing engineer. This book is very readable and highly recommended for the final-year engineering students, postgraduate engineering students and industrial engineers. For more advanced topics, readers may refer to the references below and the references therein.

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