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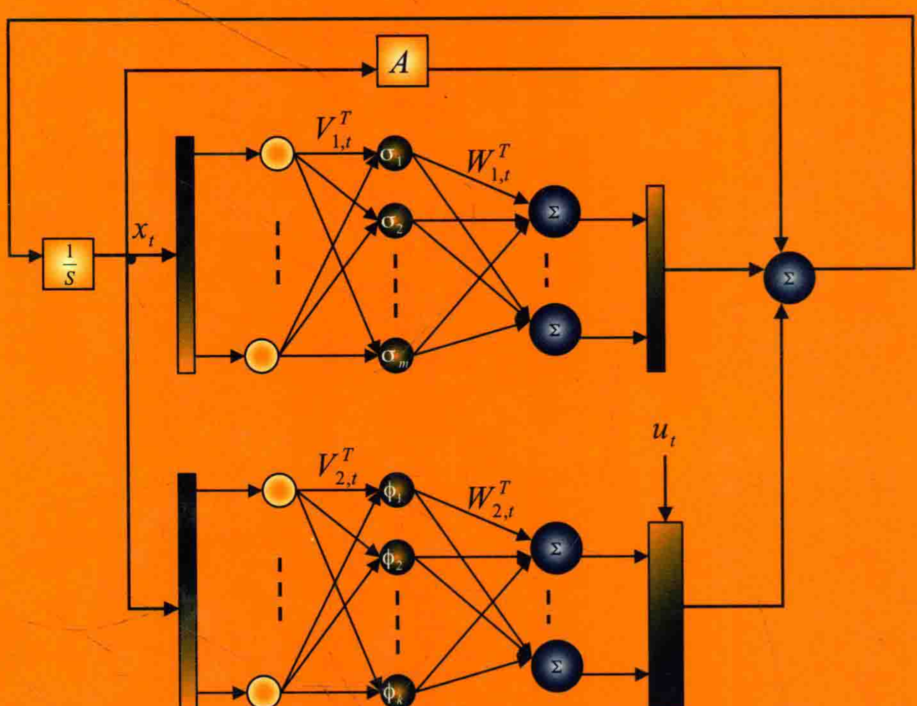
Identification, State Estimation and Trajectory Tracking



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DIFFERENTIAL NEURAL NETWORKS FOR ROBUST NONLINEAR CONTROL

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Differential Neural Networks for Robust Nonlinear Control

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To our children
Poline and Ivan,
Zulia Mayari, Ana Maria and Edgar Camilo,
Huijia and Lisa.

0.1 Abstract

This book deals with *Continuous Time Dynamic Neural Networks Theory* applied to solution of basic problems arising in Robust Control Theory including identification, state space estimation (based on neuro observers) and trajectory tracking. The plants to be identified and controlled are assumed to be a priory unknown but belonging to a given class containing internal unmodelled dynamics and external perturbations as well. The error stability analysis and the corresponding error bounds for different problems are presented. The high effectiveness of the suggested approach is illustrated by its application to various controlled physical systems (robotic, chaotic, chemical and etc.).

0.2 Preface

Due to the big enthusiasm generated by successful applications, the use of *static (feedforward) neural networks* in automatic control is well established. Although they have been used successfully, the major disadvantage is a slow learning rate. Furthermore, they do not have memory and their outputs are uniquely determined by the current value of their inputs and weights. This is a high contrast to biological neural systems which always have feedback in their operation such as the cerebellum and its associated circuitry, and the reverberating circuit, which is the basis for many of the nervous system activities.

Most of the existing results on nonlinear control are based on static (feedforward) neural networks. On the contrary, there are just a few publications related to *Dynamic Neural Networks* for Automatic Control applications, even if they offer a better structure for representing dynamic nonlinear systems.

As a natural extension of the static neural networks capability to approximate nonlinear functions, the dynamic neural networks can be used to approximate the behavior of nonlinear systems. There are some results in this directions, but their requirements are quite restrictive.

In the summer of 1994, the first two authors of this book were interested by exploring the applicability of *Dynamic Neural Networks* functioning in continuous time for Identification and Robust Control of Nonlinear Systems. The third author became involved in the summer of 1996.

Four years late, we have developed results on weights learning, identification, estimation and control based on the dynamic neural networks. Here this class of networks is named by *Differential Neural Networks* to emphasize the fact that the considered dynamic neural networks as well as the dynamic systems with incomplete information to be controlled are functioning in continuous time. These results have been published in a variety of journals and conferences. The authors wish to put together all these results within a common frame as a book.

The main aim of this book is to develop a systematic analysis for the applications of dynamic neural networks for identification, estimation and control of a wide class of nonlinear systems. The principal tool used to establish this analysis is a

Lyapunov like technique. The applicability of the results, for both identification and robust control, is illustrated by different technical examples such as: chaotic systems, robotics and chemical processes.

The book could be used for self learning as well as a textbook. The level of competence expected for the reader is that covered in the courses of differential equations, the nonlinear systems analysis, in particular, the Lyapunov methodology, and some elements of the optimization theory.

0.3 Acknowledgments

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The helpful review of Dr.Vladimir Kharitonov is greatly appreciated. Thanks are also due to anonymous reviewers of our publications, on the topics matter of this book, for their constructive criticism and helpful comments.

We want to thank the editors for their effective cooperation and great care making possible the publication of this book.

Last, but not least, we thank the time and dedication of our wives Tatyana, Maria de Lourdes, and Xiaoou. Without them this book would not be possible.

Alexander S. Poznyak
Edgar N. Sanchez
Wen Yu

Mexico, January of 2000

0.4 Introduction

Undoubtedly, since their strong rebirth in the last decade, *Artificial Neural Networks (ANN)* are playing an increasing role in Engineering. For some years, they have been seen as providing considerable promise for application in the nonlinear control. This promise is based on their theoretical capability to approximate arbitrary well continuous nonlinear mappings.

By large, the application of neural networks to automatic control is usually for building a model of the plant and, on the basis of this model, to design a control law. The main neural network structure in use is the static one or, in other word, is the feedforward type: the input-output information process, performed by the neural network, can be represented as a nonlinear algebraic mapping.

On the basis of *Static Neural Networks (SNN)* capability to approximate any nonlinear continuous function, a natural extension is to approximate the input-output behavior of nonlinear systems by *Dynamic Neural Networks (DNN)*: their information process is described by differential equations for continuous time or by difference equations for discrete time. The existing results about this extension require quite restrictive conditions such as: an open loop stability or a time belonging to a close set.

This book is intended to familiarize the reader with the new field of the dynamic neural networks applications for robust nonlinear control, that is, it develops a systematic analysis for identification, state estimation and trajectory tracking of nonlinear systems by means of Differential (Dynamic Continuous Time) Neural Networks . The main tool for this analysis is the *Lyapunov like approach.*

The book is aimed to graduate students, but the practitioner engineer can profit from it for self learning. A background in differential equations, nonlinear systems analysis, in particular Lyapunov approach, and optimization techniques is strongly recommended. The reader could read the appendices or use some of the given references to cover these topics. Therefore the book should be very useful for a wide spectrum of researchers and engineers interested in the growing field of the neuro-control, mainly based on differential neural networks.

0.4.1 Guide for the Readers

The structure of the book scheme we developed consists of two main parts:

The Identifier (or the state estimator). A differential neural network is used to build a model of the plant. We consider two cases:

a) the dimension of the neural network state consides with one of the nonlinear system; so the neural networks becomes an identifier.

b) the nonlinear system output depends linearly on the states. The neural network allows to estimate the system state by means of a neural observer implementation.

The controller. Based of the model, implemented by the neural identifier or observer, the local optimal control law is developed , which at each time minimizes the tracking error with respect to a nonlinear reference model under the fixed prehistory of this process; it also minimize the required input energy.

Additionally, in order to perform a better identification, we developed two new algorithms to adapt on-line the neural network weights. These algorithms are based on the sliding modes technique and the gradient like contribution.

The book consists of four principal parts:

- An introductory chapter (Chapter 1) reviewing the basic concepts about neural networks.
- A part related to the *neural identification* and *estimation* (Chapters 2, 3, 4).
- A part dealing with the *passivation* and the *neurocontrol* (Chapters 5 and 6).
- The last part related to its applications (Chapters 7, 8, 9 and 10).

The content of each chapter is as follows.

Chapter One: *Neural Networks Structures.* The development and the structures of Neural Networks are briefly reviewed. We first take a look to biological ones. Then the different structures classifying them as static or dynamic neural networks are discussed. In the introduction, the importance of autonomous or intelligent systems is established, and the role which neural networks could play to implement such a system for the control aims is discussed. Regarding to biological neural networks, the main phenomena, taking place in them,.are briefly described. A brief review of the different neural networks structures such as the single layer, the multi-layer perceptron, the radial basis functions, the recurrent and the differential ones, is also presented. Finally, the applications of neural networks to robust control are discussed.

Chapter Two: *Nonlinear System Identification.* The on-line nonlinear system identification, by means of a differential neural network with the same space state dimension as the system, is analyzed. It is assumed that the system space state dimension completely measurable. Based of the Lyapunov-like analysis, the stability conditions for the identification error are determined. For the identification analysis an algebraic Riccati equation is ued. The new learning law ensures the identification error convergence to zero (model matching) or to a bounded zone (with unmodelled dynamics). As our main contributions, a new on-line learning law for differential neural network weights is developed and the theorem, giving a bound for the identification error which turns out to be proportional to the a priory uncertainty bound, is established. To identify on-line a nonlinear system from a given class a new stable learning law for a differential *multilayer* neural network is also proposed. By means of a Lyapunov-like analysis the stable learning algorithms for the hidden layer as well as for the output layer is determined. An algebraic Riccati equation is used to give a bound for the identification error. The new learning is similar with the backpropagation for multilayer perceptrons. With this updating law we can assure that the identification error is globally asymptotically stable (GAS). The applicability of these results is illustrate by several numerical examples.

Chapter Three: *Sliding Mode Learning.* The identification of continuous, uncertain nonlinear systems in presence of bounded disturbances is implemented using dynamic neural networks. The proposed neural identifier guarantees a bound for the state estimation error, which turns out to be a linear combinations of the internal and external uncertainties levels. The neural network weights are updated on-line by a learning algorithm based on the sliding mode technique. To the best of authors awareness, this is the first time when such a learning scheme is proposed for differential neural networks. The numerical simulations illustrate its effectiveness even for highly nonlinear systems in the presence of important disturbances.

Chapter Four: *Neural State Estimation.* A dynamic neural network solution of the state estimation is discussed. The proposed adaptive robust neuro-observer has an extended Luneburger structure. Its weights are learned on-line by a new gradient-like algorithm. The gain matrix is calculated by solving a matrix optimization problem and an inverted solution of a differential matrix Riccati equation. In the case when the normal nonlinear system is a priory unknown, the state observation using dynamic recurrent neural network, for continuous time, uncertain nonlinear systems, subjected to external and internal disturbances of bounded power, is discussed. The design of a suboptimal neuro-observer is proposed to achieve a perspectives accuracy of the estimation error, which is defined as the weighted squares of its semi-norm. This error turns out to be a linear combination of the power levels of the external disturbances and internal uncertainties. The numerical simulations of the proposed robust observer illustrate its effectiveness in the presence of the unmodelled uncertainties of a high level.

Chapter Five: *Passivation via Neuro Control.* An adaptive technique is suggested to provide the passivity property for a class of partially known SISO nonlinear systems. A simple differencial neural network (DifNN), containing only two neurons, is used to identify the unknown nonlinear system. By means of a Lyapunov-like analysis a new learning law is derived for this DifNN guarantying both a successful identification and passivation effects. Based on this adaptive DifNN model an adaptive feedback controller, serving for wide class of nonlinear systems with a priory incomplete model description, is designed. Two typical examples illustrate the effectiveness of the suggested approach.

Chapter Six: *Nonlinear System Tracking.* If the state measurements of a nonlinear system are available and its structure is estimated by a dynamic neural identifier or neuro-observer, to track a reference nonlinear model an optimal control law can be developed. To do that, first a neuro identifier is considered and, using the on-line adapted parameter of the corresponding differential neural network, an optimal control law is implemented. It minimizes the input energy and the tracking error between the designed DifNN and a given reference model. Then, assuming that not all the system states are measurable, the above discussed neuro-observer is implemented . The optimal control law has the same structure as before, but with the space states replaced by their estimates. In both cases a bound for the trajectory error is guaranteed. So, the control scheme is based on the proposed neuro-observer and, as a result, the final structure is composed by two parts: the neuro-observer and the tracking controller. Some simulation results conclude this chapter.

Chapter Seven: *Neural Control for Chaos.* Control for a wide class of continuous time nonlinear systems with unknown dynamic description (model) can be implemented using a dynamic neural approach. This class includes a wide group of chaotic systems which are assumed to have unpredictable behavior but whose state can be measured. The proposed control structure has to main parts: a neural identifier and a neural controller. The weights of the neural identifier are updated on-line by a learning algorithm based on the sliding mode technique. The controller assures tracking of a reference model. Bounds for both the identification and the tracking errors are established. So, in this chapter identification and control of unknown chaotic dynamical systems are consider. Our aim is to regulate the unknown chaos to a fixed points or a stable periodic orbits. This is realized by following two contributions: first, a dynamic neural network is used as identifier. The weights of the neural networks are updated by the sliding mode technique. This neuro-identifier guarantees the boundedness of identification error. Secondly, we derive a local optimal controller via the neuro-identifier to remove the chaos in a system. The controller proposed in this chapter is effective for many chaotic systems including Lorenz system, Duffing equation and Chua's circuit.

Chapter Eight: *Neuro Control for Robot Manipulator.* The neuro tracking problem for a robot manipulator with two degrees of mobility and with unknown load, friction and the parameters of the mechanical system , subject to variations within a given interval, is tackled. The design of the neuro robust nonlinear controller is proposed such a way that a certain accuracy of the tracking is achieved. The suggested neuro controller has a direct linearization part and a locally optimal compensator. Compared with sliding mode type and linear state feedback controllers, numerical simulations of this robust controller illustrate its effectiveness.

Chapter Nine: *Identification of Chemical Processes.* The identification problem for multicomponent nonstationary ozonization processes with incomplete observable states is addressed. The corresponding mathematical model containing unknown parameters is used to simplify the initial nonlinear model and to derive its observability conditions. To estimate the current concentration of each component, a dynamic neuro observer is suggested. Based on the obtained neuro observer outputs, the continuous time version of LS-algorithm, supplied by special projection procedure, is applied to construct the estimates of unknown chemical reaction constants. Simulation results related to the identification of ozonization process illustrate the applicability of the suggested approach.

Chapter Ten: *Neuro Control for a Multicomponent Distillation Column.* Control of a multicomponent non-ideal distillation column is proposed by using a dynamic neural network approach. The holdup, liquid and vapor flow rates are assumed to be time-varying, that is, the non-ideal conditions are considered. The control scheme is composed of two parts: a dynamic neural observer and a neuro controller for output trajectory tracking. Bounds for both the state estimation and the tracking errors are guaranteed. The trajectory to be tracked is generated by a reference model, which could be nonlinear. The controller structure which we propose is composed of two parts: the neuro-identifier and the local optimal controller. Numerical simulations, concerning a 5 components distillation column with 15 trays, illustrate the high effectiveness of the approach suggested in this chapter.

Three appendices end the book containing some auxiliary mathematical results:

Appendix A deals with some useful mathematical facts;

Appendix B contains the basis required to understand the Lyapunov-like approach used to derive the results obtain within this book;

Appendix C discusses some definitions and properties concerning to the locally optimization technique required to obtain the mentioned optimal control law.

0.5 Notations

":= " this symbol means "equal by definition";

$x_t \in \Re^n$ is the state vector of the system at time $t \in R^+ := \{t : t \geq 0\}$;

$\widehat{x}_t \in \Re^n$ is the state of the neural network;

x^* is the state of nonlinear reference model;

$u_t \in \Re^q$ is a given control action;

$y_t \in \Re^m$ is the output vector;

$f(x_t, u_t, t) : \Re^{n+q+1} \to \Re^n$ is a vector valued nonlinear function describing the system dynamics;

$\varphi(x^*, t) : \Re^{n+1} \to \Re^n$ is nonlinear reference model;

$C \in \Re^{n \times m}$ is the unknown output matrix;

$\xi_{1,t}$, $\xi_{2,t}$ are vector-functions representing external perturbations;

Υ_1, Υ_2 are the "bounded power" of $\xi_{1,t}$, $\xi_{2,t}$;

$A \in \Re^{n \times n}$ is a Hurtwitz (stable) matrix;

$W_{1,t} \in \Re^{n \times k}$ is the weights matrix for nonlinear state feedback;

$W_{2,t} \in \Re^{n \times r}$ is the input weights matrix;

W_1^* and W_2^* are the initial values for $W_{1,t}$ and $W_{2,t}$;

$\overline{W}_1$ and $\overline{W}_2$ are wieghted upper bounds for $W_{1,t}$ and $W_{2,t}$;

$\widetilde{W}_1$ and $\widetilde{W}_2$ are the weight estimation error of $W_{1,t}$ and $W_{2,t}$;

$K_t \in \Re^{n \times m}$ is the observer gain matrix;

$\phi(\cdot)$ is a diagonal matrix function;

$\sigma(\cdot)$ and $\gamma(.)$ are $n-$dimensional vector functions;

$\widetilde{\sigma}_t := \sigma(x_t) - \sigma(\widehat{x}_t)$, $\widetilde{\phi}_t := \phi(x_t) - \phi(\widehat{x}_t)$;

Δ_t is the identification error;

$\triangle f$ is the modeling error reflecting the effect of unmodelled dynamics;

L_i is the Liptshitz constant for the function $f(x) : R^n \xrightarrow{f} R^m$

$$\|f(x) - f(y)\| \leq L_i \|x - y\|, \quad \forall x, y \in \Re^n, \quad L_i \in [0, \infty);$$

$\overline{\lim\limits_{t\to\infty}}$ is the upper limit:

$$\overline{\lim_{t\to\infty}} x_t := \lim_{t\to\infty} \sup x_t = \lim_{t\to\infty} \sup_{n\geq t} x_n;$$

$\|\cdot\|$ is the Euclidian norm for vectors, and for any matrix A it is defined as

$$\|A\| := \sqrt{\lambda_{\max}(A^T A)};$$

$\lambda_{\max}(.)$ is the maximum eigenvalue of the respective matrix;

$\|\cdot\|_W$ is the weighted Euclidian norm of the vector $x \in R^n$:

$$\|\cdot\|_W := \sqrt{\sum_{i=1}^{n} w_i x_i^2};$$

$\|\cdot\|_Q$ is the semi-norms of a function, defined as

$$\|x\|_Q := \sqrt{\overline{\lim_{T\to\infty}} \frac{1}{T} \int_0^T x_t^T Q x_t dt};$$

$[\bullet]^+$ is the pseudoinverse matrix in Moor-Penrose sense, satisfing:

$$A^+ A A^+ = A^+, \quad A A^+ A = A$$