NEURAL SYSTEMS FOR CONTROL

Edited by

Omid Omidvar

David L. Elliott

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Omid Omidvar
University of the District of Columbia

David L. Elliott
University of Maryland

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Contributors

- Andrew G. Barto*
  Department of Computer Science
  University of Massachusetts
  Amherst, MA 01003, USA
  E-mail: barto@cs.umass.edu

- William J. Byrne*
  Center for Language and Speech Processing, Barton Hall
  Johns Hopkins University
  Baltimore, MD 21218, USA
  E-mail: byrne@cspjhu.ece.jhu.edu

- Sungzoon Cho*
  Department of Computer Science and Engineering
  POSTECH Information Research Laboratories
  Pohang University of Science and Technology
  San 31 Hyojadong
  Pohang, Kyungbook 790-784, South Korea
  E-mail: zoon@zoon.postech.ac.kr

- Francis J. Doyle III*
  School of Chemical Engineering
  Purdue University
  West Lafayette, IN 47907-1283, USA
  E-mail: fdoyle@ecn.purdue.edu

- David L. Elliott*
  Institute for Systems Research
  University of Maryland
  College Park, MD 20742, USA
  E-mail: delliott@isr.umd.edu

- Michael A. Henson
  Department of Chemical Engineering
  Louisiana State University
  Baton Rouge, LA 70803-7303, USA
  E-mail: henson@nlc.che.lsu.edu

- S. Jagannathan
  Controls Research, Caterpillar, Inc.

Tech. Ctr. Bldg. "E", M/S 855
14009 Old Galena Rd.
Mossville, IL 61552, USA
E-mail: saranj@cat.com

- Min Jang
  Department of Computer Science and Engineering
  POSTECH Information Research Laboratories
  Pohang University of Science and Technology
  San 31 Hyojadong
  Pohang, Kyungbook 790-784, South Korea
  E-mail: jmin@zoon.postech.ac.kr

- Asriel U. Levin*
  Wells Fargo Nikko Investment Advisors, Advanced Strategies and Research Group
  45 Fremont Street
  San Francisco, CA 94105, USA
  E-mail: asriel.levin@bglobal.com

- Frank L. Lewis*
  Automation and Robotics Research Institute
  University of Texas at Arlington
  7300 Jack Newell Blvd. S
  Fort Worth, TX 76118, USA
  E-mail: flewis@arrirs04.uta.edu

- Kumpati S. Narendra
  Center for Systems Science
  Department of Electrical Engineering
  Yale University
  New Haven, CT 06520, USA
  E-mail: Narendra@koshy.eng.yale.edu

- Babatunde A. Ogunnaike
  Neural Computation Program, Strategic Process Technology Group
  E. I. Dupont de Nemours and Company
  Wilmington, DE 19880-0101, USA
  E-mail: ogunnaike@esspt0.dnet.dupont.com

- Omid M. Omidvar
  Computer Science Department
  University of the District of Columbia
  Washington, DC 20008, USA
  E-mail: oomidvar@udcvax.bitnet

- Thomas Parisini*
  Department of Electrical, Electronic and Computer Engineering

DEEI–University of Trieste, Via Valerio 10, 34175 Trieste, Italy
E-mail: thomas@dist.dist.unige.it

- S. Joe Qin*
Department of Chemical Engineering, Campus Mail Code C0400
University of Texas
Austin, TX 78712, USA
E-mail: qin@che.utexas.edu

- James A. Reggia*
Department of Computer Science, Department of Neurology, and Institute for Advanced Computer Studies
University of Maryland
College Park, MD 20742, USA
E-mail: reggia@avion.cs.umd.edu

- Ilya Rybak
Neural Computation Program, Strategic Process Technology Group
E. I. Dupont de Nemours and Company
Wilmington, DE 19880-0101, USA
E-mail: rybaki@eplrx7.es.dupont.com

- Tariq Samad
Honeywell Technology Center
Honeywell Inc.
3660 Technology Drive, MN65-2600
Minneapolis, MN 55418, USA
E-mail: samad@htc.honeywell.com

- Clemens Schäffner*
Siemens AG
Corporate Research and Development, ZFE T SN 4
Otto–Hahn–Ring 6
D – 81730 Munich, Germany
E-mail: Clemens.Schaeffner@zfe.siemens.de

- Dierk Schröder
Institute for Electrical Drives
Technical University of Munich
Arcisstrasse 21, D – 80333 Munich, Germany
E-mail: eat@e-technik.tu-muenchen.de

- James A. Schwaber
Neural Computation Program, Strategic Process Technology Group
E. I. Dupont de Nemours and Company
Wilmington, DE 19880-0101, USA
E-mail: schwaber@eplrx7.es.dupont.com

- Shihab A. Shamma
  Electrical Engineering Department and the Institute for Systems Research
  University of Maryland
  College Park, MD 20742, USA
  E-mail: sas@isr.umd.edu

- H. Ted Su*
  Honeywell Technology Center
  Honeywell Inc.
  3660 Technology Drive, MN65-2600
  Minneapolis, MN 55418, USA
  E-mail: tedsu@htc.honeywell.com

- Gary G. Yen*
  USAF Phillips Laboratory, Structures and Controls Division
  3550 Aberdeen Avenue, S.E.
  Kirtland AFB, NM 87117, USA
  E-mail: yeng@plk.af.mil

- Aydin Yeşildirek
  Measurement and Control Engineering Research Center
  College of Engineering
  Idaho State University
  Pocatello, ID 83209-8060, USA
  E-mail: yesiaydi@fs.isu.edu

- Riccardo Zoppoli
  Department of Communications, Computer and System Sciences
  University of Genoa, Via Opera Pia 11A
  16145 Genova, Italy
  E-mail: rzop@dist.unige.it

* Corresponding Author

Preface

If you are acquainted with neural networks, you will find that automatic control problems provide applications — industrially useful — of your knowledge, and that they have a dynamic or evolutionary nature lacking in static pattern-recognition. Control ideas are also prevalent in the study of the natural neural networks found in animals and human beings.

If you are interested in the practice and theory of control, you will find that artificial neural networks offer a way to synthesize nonlinear controllers, filters, state observers and system identifiers using a parallel method of computation.

The purpose of this book is to acquaint those in either field with current research involving both. The book project originated with O. M. Omidvar. Chapters were obtained by an open call for papers and by invitation. The topics requested included mathematical foundations; biological control architectures; applications of neural network control methods (neurocontrol) in high technology, process control, and manufacturing; reinforcement learning; and neural network approximations to optimal control. The responses included leading edge research, exciting applications, surveys and tutorials to guide the reader who needs pointers for research or application. The authors' addresses are given in the Contributors list; their work represents both academic and industrial thinking.

This book is intended for a wide audience — those professionally involved in neural network research, such as lecturers and primary investigators in neural computing, neural modeling, neural learning, neural memory, and neurocomputers. *Neural Systems for Control* focuses on research in natural and artificial neural systems directly applicable to control or making use of modern control theory.

Each of the chapters was refereed; we are grateful to those anonymous referees for their careful work.

Omid M. Omidvar, University of the District of Columbia

David L. Elliott, University of Maryland, College Park

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Chapter 1

Introduction: Neural Networks and Automatic Control

David L. Elliott

1 Control Systems

Through the years artificial neural networks (Frank Rosenblatt's *perceptrons*, Bernard Widrow's *adalines*, Albus' CMAC) have been invented with both biological ideas and control applications in mind, and the theories of the brain and nervous system have used ideas from control system theory (e.g. Norbert Wiener's *cybernetics*). This book attempts to show how the control system and neural network researchers of the present day are cooperating. Since members of both communities like signal flow charts, I will use a few of these schematic diagrams to introduce some basic ideas.

Figure 1 is a stereotypical control system. (The dashed lines with arrows indicate the flow of signals; Σ is a summing junction where the feedback is subtracted from the command to obtain an error signal.)

One box in the diagram is usually called the plant, or the object of control. It might be a manufactured object like the engine in your automobile, or it might be your heart–lung system. The arrow labeled *command* then might be the accelerator pedal of the car, or a chemical message from your brain to your glands when you perceive danger — in either case the command being to increase the speed of some chemical or mechanical process. The *output* is the controlled quantity. It could be the engine revolutions-per-minute, which shows on the tachometer; or it could be the blood flow

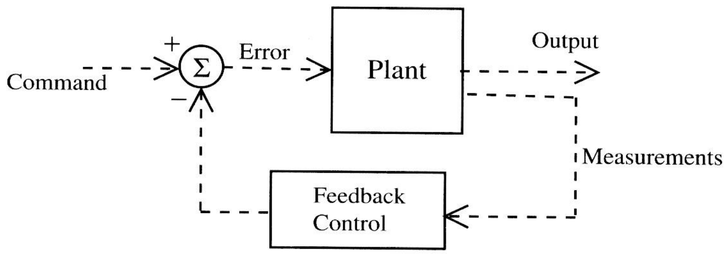

FIGURE 1. Control system.

to your tissues. The measurements of the internal state of the plant might include the output plus other engine variables (manifold pressure for instance) or physiological variables (blood pressure, heart rate, blood carbon dioxide). As the plant responds to the command, somewhere under the car's hood or in your body's neurochemistry, a local *feedback* control may use these measurements to regulate the response.

Automobile design engineers may try, perhaps using electronic fuel injection, to give you fuel economy and keep the emissions of unburnt fuel low at the same time; such a design uses modern control principles, and the automobile industry is beginning to implement these ideas with neural networks.

To be able to use mathematical or computational methods to improve the control system's response to its input command, the plant and the feedback controller are modeled mathematically by differential equations, difference equations, or, as will be seen, by a neural network with internal time lags as in Chapter 6.

Some of the models in this book are industrial rolling mills (Chapter 9), a small space robot (Chapter 12), robot arms (Chapter 7), and in Chapter 11 aerospace vehicles that must adapt or reconfigure their controls after the system has changed, perhaps from damage. Industrial control is often a matter of adjusting one or more simple controllers capable of supplying feedback proportional to error, accumulated error ("integral"), and rate of change of error ("derivative")—a so-called PID controller. Methods of replacing these familiar controllers with a neural network–based device are shown in Chapter 10.

The motivation for control system design is often to optimize a cost, such as the energy used or the time taken for a control action. Control designed for minimum cost is called *optimal control.*

The problem of approximating optimal control in a practical way can be attacked with neural network methods, as in Chapter 12; its authors, control theorists, use the new "receding-horizon" approach of Mayne and Michalska. Chapter 7 also is concerned with control optimization by neural network methods. One type of optimization (achieving a goal as fast as possible under constraints) is applied by such methods to the real industrial problem of Chapter 9.

The control systems in our bodies, such as sensory, pulmonary and circulatory systems, have evolved well enough to keep us alive and running in a dangerous world. Control aspects of the human nervous system are addressed in Chapters 3, 4, and 5. Chapter 3 is from a team using neural networks in signal processing; it shows some ways that speech processing may be simulated and sequences of phonemes recognized using *hidden Markov* methods. Chapter 4, whose authors work in neurology and computer science, uses a neural network with inputs from a model of the human arm to see how the arm's motions may map to the cerebral cortex in a computational way. Chapter 5, which was written by a team representing control engineering, chemical engineering, and human physiology, examines the workings of blood pressure control (the vagal baroreceptor reflex) and shows how to mimic this control system for chemical process applications.

2 What is a Neural Network?

The "neural networks" referred to in this book are *artificial neural networks*, a technique for using physical hardware or computer software to model computational properties analogous to some that have been postulated for real networks of nerves, such as the ability to learn and store relationships. A neural network can efficiently approximate and interpolate multivariate data that might otherwise require huge databases; such techniques are now well accepted for nonlinear statistical fitting and prediction ("ridge regression").

A commonly used artificial neuron, shown in Figure 2, is a simple structure, having just one nonlinear function of a weighted sum of several data inputs $x_1, \ldots, x_n$; this version, often called a *perceptron*, computes what statisticians call a ridge function (as in "ridge regression"),

$$y = \sigma(w_0 + \sum_{i=1}^{n} w_i x_i),$$

and for the discussion below assume that the function σ is a smooth, increasing, bounded function.

Examples of sigmoid functions (so called from their "S" shape) in common use are

$$\begin{aligned}\sigma_1(u) &= \tanh(u),\\ \sigma_2(u) &= 1/(1+\exp(-u)),\\ \sigma_3(u) &= u/(1+|u|).\end{aligned}$$

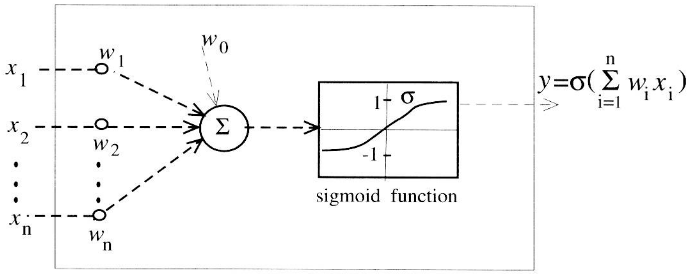

FIGURE 2. Feedforward neuron.

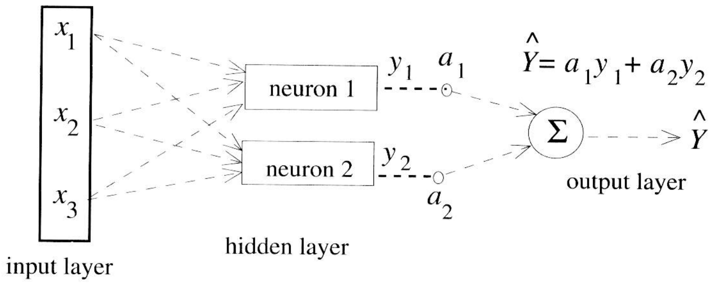

FIGURE 3. A small feedforward network.

The weight-adjustment algorithm will use the derivatives of these sigmoid functions, which are easily evaluated for the examples we have listed by using the differential equations they satisfy:

$$\begin{aligned}
\sigma_1' &= 1 - (\sigma_1)^2, \\
\sigma_2' &= \sigma_2(1 - \sigma_2), \\
\sigma_3' &= (1 - |\sigma_3|)^2.
\end{aligned}$$

Statisticians use many other such functions, including sinusoids. In proofs of the adequacy of neural networks to represent quite general smooth functions of many variables, the sinusoids are an important tool.

The weights w_i are to be selected or adjusted to make this ridge function approximate some function which may or may not be known in advance. The basic principles of weight adjustment were originally motivated by ideas from the psychology of learning (see Chapter 2).

In order to learn functions more complex than ridge functions, one must use networks of perceptrons. The simple example of Figure 3 shows a *feedforward perceptron network*, the kind you will find most often in the following chapters.[1] Thus the general idea of feedforward networks is that they allow us to realize functions of many variables by adjusting the network weights. Here is a typical scenario corresponding to Figure 2:

- From experiment, obtain numerical data samples of each of three different "input" variables, which we arrange as an array $X = (x_1, x_2, x_3)$, and an "output" variable Y that has a functional relation to the inputs, $Y = F(X)$.

- X is used as input to two perceptrons with adjustable weight arrays $[w_{1j}, w_{2j} : j = 1, 2, 3]$; their outputs are y_1, y_2.

- This network's single output is $\hat{Y} = a_1 y_1 + a_2 y_2$, where a_1, a_2 can

[1]There are several other kinds of neural network in the book, such as CMAC and radial basis function networks.