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BOOK REVIEW

Neural Networks for Control

Edited by T. Miller, R. S. Sutton, and P. J. Werbos, MIT Press, Cambridge, MA: 1990, hardcover $49.95, 524 pp., ISBN 0-262-13261-3.

Neural Networks for Control is based on a workshop entitled "The Application of Neural Networks to Robotics and Control" held in October 1988[1] at the University of New Hampshire. Consistent with the varied backgrounds of the workshop attendees, this collection of works endeavors not only to present current theoretical research in neural network-based control systems, but also aims to identify industrial applications where neural networks may prove useful in the near future. The book is broken into three parts: (I) general principles, (II) motion control, and (III) application domains. In addition, eight benchmark control problems are included in an appendix. The main theme pervading this effort concerns the synthesis of neural network methods with existing knowledge from the well-studied fields of conventional and adaptive control theory. Perhaps due to the focus on engineering control theory, little direct contact is made with issues involving control in biological systems.

Control problems arise when we try to make a physical system exhibit a desired response. If we know the functions relating inputs to outputs and vice versa for the system, we can use these functions to predict system behavior and control the system's response by judicious choice of inputs. Unfortunately, most complex systems exhibit highly nonlinear input-output functions. Moreover, because the complexity of such systems is often necessary for their intended function (e.g., controlling the position and orientation of a hand in 3-D space requires at least a 6 degree-of-freedom "arm") the input-output function of the system cannot be simplified. Therefore, it becomes necessary to solve a difficult prediction problem as a preliminary to effective control.

A classical approach to predicting the behavior of such systems is to "open up the black box" (i.e., to build a model of the system that captures its constituent structure and the elementary functions describing interactions among the constituents). An accurate model allows the overall input-output function to be computed as a composition of more elementary functions. Moreover, to paraphrase the Swiss structuralist Piaget, "to understand is to reconstruct." The description of the constituent structure taken together with the local laws of interaction provide an understanding of the mechanisms by which the aggregate input-output function is generated.

However, another path can be taken to predicting the response of a system exhibiting a highly nonlinear input-output function: perform a variety of nonlinear regression analysis, or least-squares curve fitting, on a sufficiently broad sample of input-output pairs. Such an analysis can often yield sufficiently accurate predictions to allow effective control but may lead to little real understanding of the system being controlled.

Corresponding to these two approaches to prediction, there are two ways that neural network studies can contribute to control theory. First, in what we will call type I applications, neural network studies provide new ideas for implementing the classical approach to control through modeling. In other words, studies of this type identify neural subsystems (e.g., individual neurons or pools of neurons) and describe the interactions between these subsystems which produce the overall system behavior. For example, recent neural network studies of the computational implications of the complexly structured spinomuscular system of mammals (Bullock & Grossberg, 1990) have revealed how its global circuit design compensates for necessary local nonlinearities in such a way that the spinomuscular system appears to be a near-linear system to higher brain centers. The result is that these higher centers can control joint compliances independently from joint positions without solving a difficult prediction problem. On the other hand, in what we will call type II applications, neural network studies provide new methods for prediction by performing the equivalent of multivariate nonlinear curve fitting. Here, the back-propagation learning technique has been most widely used to date because of its well-known ability to synthesize a network that can mimic arbitrary nonlinear vector functions.

There is nothing problematic about type I applications of neural network studies to control theory. However, because control engineers trained in the classical method expect to understand why a given control strategy is effective for a given controlled system, they may be reluctant to use type II applications of neural networks. Advocates of the latter often claim it as an advantage that a network-based controller can converge to a solution even though it knows nothing of the first principles governing the controlled system's behavior. However, from the classical perspective, it is an admission of defeat to say that "it works, in the sense that the error has been eliminated by learning, but we do not know why." As rejoinder to this concern, many advocates of type II applications would argue that every engineer, qua biological entity, is living proof that type II applications can serve as a foundation for robust control systems. Such an argument rests on the supposition that the higher brain controls the body's effector systems without benefit of internal models with structures corresponding to those that might be built from first principles. Instead, the brain is supposed to rely on "brute force" associative learning of arbitrary nonlinear functions.

The most direct treatment of these and related issues appears in the chapter by Andrew Barto, which the editors wisely placed first in the volume. Barto stakes out a middle ground between physical model classicists and advocates of type II applications. At one point he writes

> it is . . . desirable to maintain high standards of mathematical rigor, but an experimental, heuristic approach seems essential for developing applications involving complex nonlinear systems and for detecting

[1] Despite the 1988 date of the workshop, references as recent as 1990 can be found in the book.

the regularities over classes of problems that can guide rigorous mathematical development. (p. 9)

This theme concerning the heuristic nature of type II neural network approaches is reiterated several times in later chapters. Later, however, Barto cautions against excessively high expectations from applications of back propagation, which he takes to be limited by a generality/generalization tradeoff:

It is because of representational restrictions built into a class of models that correct generalization can occur if the class of models happens to be appropriate to the task. To the extent that a class of models can represent any structure, it cannot be expected to produce meaningful extrapolations beyond the data on which it was trained. (p. 25)

Here he is arguing that because back propagation networks achieve their success vis-a-vis a training set of input-output pairs without necessarily capturing the constituent structure of the "modeled" system, they may be unable to generalize beyond the training set. Nevertheless, he sees back propagation as on the same continuum as classical modeling: whereas classical modeling sits on the end of the continuum where representational restrictions are high, BP sits on the end of the continuum where such restrictions are low.

In addition to providing an excellent introduction to the field through his lucid treatment of these issues, Barto furnishes a useful framework for understanding the more specialized chapters which follow. The key component of this framework is a description of five supervised learning schemes which arise repeatedly in the following chapters.

Chapter 3 by Paul Werbos, now widely acknowledged as the inventor of back propagation methods in Werbos (1974), primarily investigates the use of "adaptive critics" in reinforcement learning with emphasis on the relation between these critics and the control theory method of dynamic programming. This chapter will be most rewarding after a review of standard dynamic programming algorithms since the author spends little time expositing basic ideas.

Chapter 4 by Ronald Williams presents a well-written introduction to recurrent networks with primary emphasis on gradient descent methods for training these networks. Williams outlines the back propagation-through-time and the real-time recurrent learning algorithms. In addition, Williams includes a philosophical discussion of possible approaches to using neural networks for control, taking care to tie these concepts to those introduced by Barto in chapter 1 as well as to concepts from traditional control theory. Williams particularly emphasizes what he terms a *radical approach* within which connectionist models are used to model systems whose state cannot be determined by a fixed set of finitely many past values of its input and output. According to Williams, the radical approach has no natural counterpart in the realm of adaptive linear filters; recurrent networks, however, are well-suited to model such systems. This approach thus provides the largest potential for novel contribution by neural network methods.

In chapter 5, Kumpati Narendra directly addresses the major theme of this book; namely, he investigates the use of well-understood adaptive control techniques for studying neural network control schemes. Narendra describes in greater detail some of the supervised learning schemes introduced by Barto, focusing on the use of back propagation networks as natural substitutes for the adaptive components already found within standard adaptive control systems. In summary, Narendra makes an assertion consistent with the views of several other authors in this book: a well-developed theory of control using neural networks will require solution of many outstanding problems such as system stability, but current simulation results indicating the effectiveness of such systems on difficult control problems provides ample justification for continued study of these problems.

One of the few chapters actually comparing a neural network to standard adaptive alternatives is chapter 6 by Gordon Kraft III and David Campagna. This chapter reports the results of a comparison between a Cerebellar Model Arithmetic Computer (CMAC) neural network design and two traditional control methods, the Self-Tuning Regulator (STR), and the Lyapunov Model Reference Adaptive Controller (MRAC), on a signal tracking task using linear and nonlinear plants. The authors conclude that the CMAC compares favorably on three criteria: nonrestriction to linear systems, noise rejection, and implementation speed for real-time control. However, it compared unfavorably on convergence rate, presumably because the adaptive task for both other controllers was restricted to estimating the values of parameters in a pre-existing model.

David F. Shanno provides oft-overlooked alternatives to the steepest descent methods typically used to train neural networks in chapter 7. Included are Newton, quasi-Newton, and conjugate gradient methods for parameter estimation in large-scale optimization problems. Pointers are given to more complete treatments of these methods in the numerical algorithms literature. Although cheap and easy to implement, steepest descent methods can suffer from extremely slow convergence. These alternatives can provide much faster convergence with varying computational and memory requirements.

Convergence time surfaces as an important theme once again in chapter 8, the final chapter in the general principles section of the book. Here Richard Sutton constructs a simple adaptive path planner to illustrate the large benefits that can accrue when what the early cognitive psychologist Tolman (1932) called "vicarious trial and error" is combined with a reinforcement learning rule suitable for temporal credit assignment. Like the adaptive critic approach described by Werbos in chapter 3, this planner, called Dyna, is based on dynamic programming principles from control theory. Sutton describes results of a study which shows that a system able to "perform" trial and error actions both in the world and in imagination (with the aid of an internalized world model) converges much more quickly to an optimal policy than a system restricted to performance in the world. Because this chapter is intended to present general neural network control principles, it is unfortunate that primary emphasis is on a particular planning model with too little discussion of possible implications and applications of the ideas inherent to this model for neural network control.

In chapter 9 Mitsuo Kawato initiates the section on motion planning with a survey that encompasses both inverse kinematics and inverse dynamics, but with an emphasis on the latter. Kawato is well-known for his work on combining feedback controllers with adaptive feedforward controllers that are trained by the error signals arising within the feedback controller. Though he has explored a wide range of network designs, an enduring aspect of his approach since at least 1987 is based on the hypothesis that in the brain the cerebellum is an error-trained feedforward controller. An idea pursued in the work of Kawato and others (e.g., Grossberg & Kuperstein, 1986; Ito, 1984), directly inspired by the location of the cerebellum as a reconvergent sidepath for signals also sent more directly to motoneurons, is that it is often not necessary for effective control to learn the function for the forward dynamics of a controlled system. Instead, one can simply input the desired kinematics to both a low-gain feedback controller and an initially low-gain feedforward controller, and use the error signals from the feedback controller to slowly increment gains through the sidepath-feedforward controller. Eventually, the feedback controller is largely "unloaded" because the predictable component of its work load has been taken over by the feedforward controller, which has learned the inverse dynamics (i.e., the mapping between desired trajectory and force-generating signals adequate to realize that trajectory). Designs for this kind of autonomous supersession of control allow a system to be robust in nonstationary environments. The robustness derives from the existence of a fallback mode (e.g., low-gain feedback control, or overt trial and error) that can reassume the burden of control when predictions based on once valid, or elsewhere valid, parameter settings begin to fail. In the current work, Kawato addresses the ill-posedness (i.e., nonexistence of a unique solution) inherent to the problems of trajectory formation, inverse kinematics, and inverse dynamics. Different models for learning inverse dynamics are discussed with emphasis on their ability to cope with this ill-posedness.

In chapter 10, Bartlett Mel continues the theme of vicarious trial and error raised in Sutton's contribution. He explores a system in which the primary mapping learned from experience and applied during performance is a forward kinematics mapping from initial states and unit joint angle perturbations to implied motions of a robot arm. His robotic system uses this learned map to "mentally" search for an arm trajectory capable of bridging the gap between an initial and a desired endpoint position without having any part of the arm collide with obstacles. This task is simplified relative to standard techniques by eschewing all explicit geometric computations and relying on iterative use of the learned map to generate a visual representation of the expected 2-D area displaced by the arm following a candidate vector of unit joint rotations. This visual representation arises within the same visual representation field used to register the positions of obstacles, so an expected collision is specified by overlap of imagined arm and actual object. Mel argues that because explicit geometric modeling is so compute-intensive, replacement of classical geometric modeling by a neural map might yield a large performance gain. Mel's method of sensory-based motion planning which trades optimality for ease of computation represents an approach to neural network control which is radically different from any other in the book.

In chapter 11, Christopher Atkeson and David Reinkensmeyer discuss the use of associative content-addressable memories (ACAMs) in a simple control scheme which stores "experiences" in a memory, then uses a parallel search during performance to find the stored experience which best matches current needs. Although simpler than the CMAC, this system sacrifices the CMAC property of automatic generalization arising from continuity and overlapping receptive fields. Nonetheless, the modestly-named "feasibility studies" summarized in this chapter show reasonable performance with one caveat: possibly due to the lack of generalization, the system often gets stuck on performance plateaus well before errors approach zero. Although not implemented with neural networks in this chapter, Atkeson and Reinkensmeyer discuss possible neural network implementations of ACAMs.

Control of a simulation for backing up tractor-trailer trucks is addressed by Derrick Nguyen and Bernard Widrow in chapter 12. The truck backer-upper uses a common control scheme introduced in Barto's chapter to learn to back a truck from an arbitrary initial position to a loading dock, a difficult nonlinear control problem which this backprop-based model learns through several thousand training trials. The specifics of this control problem are presented as one of the benchmark problems in the appendix.

No collection of papers on neural networks for control would be complete without a chapter that focuses on the cerebellum. The reason is simple; the cerebellum contains roughly half the cells in a human brain. It receives diverse spinal and cortical inputs, and the vast majority of its output cells project to motoneurons over pathways with only a few interposed synapses; moreover, the internal circuitry of the cerebellum suggests a huge array of nearly identical processing units. Thus, to explain the key computational role of the cerebellum is simultaneously to explain half the brain and to characterize the nature of evolution's solution to the BIG PROBLEM in motor control as it has existed for vertebrate animals. A long series of computational proposals have been made by physiologists and neural network theorists, and many have been partially supported by experimental data. In chapter 13, James Houk, Satinder Singh, Charles Fisher, and Andrew Barto sketch another new proposal regarding computational functions of the cerebellum, with an emphasis on how it may act in concert with peri-cerebellar circuitry. This proposal assumes the thesis common to Ito (1984), Kawato (chapter 9), Grossberg and Kuperstein (1986), Fujita (1982), and many others that error signals returned to the cerebellar cortex via climbing fibers help modify synaptic weights from parallel fibers onto Purkinje cells and thereby modify the level of inhibition exerted by Purkinje cells on motor pathways. The novel aspects of the current proposal are (a) that Purkinje cells inhibit positive feedback loops among reticular neurons, red nucleus cells, and deep cerebellar nuclear cells and (b) that the resultant composite circuit serves as a trajectory generator. This proposal has been questioned elsewhere (see Bullock & Grossberg, 1991).

As the lone representative of neural network research aimed at discovering the methods of neural motor control through direct study of biology, this chapter is an important contribution to the book. Unfortunately, however, it is misleading at times. For example, the simulations used to illustrate the model do not address the fundamental question of how the transformation from sensory input to motor output (stressed as a key function of the cerebellum by the authors) is performed. Demonstration of the model's sufficiency for performing this transformation—which requires processing input represented in one coordinate frame to produce output in another coordinate frame—is totally obscured due to identical coordinate representations of the sensory and motor signals in the 1-D example. The chapter also contains inaccuracies that may mislead readers unfamiliar with physiology and/or alternative models. Two of these occur in the following passage:

> Bullock and Grossberg instead postulate that a similar error signal is fed into a time-varying gain function specifically tailored to produce symmetrical velocity profiles. The time-varying gain starts out at zero and grows in an uneven manner that was chosen specifically to produce symmetrical velocity profiles. The purpose of doing this is not entirely clear, since recordings from brain cells that transmit motor commands generally show abrupt onsets and off-sets. (p. 341)

In fact, however, the time-varying gain function of Bullock and Grossberg (1988) grows smoothly and monotonically (the symmetrical velocity profiles resulting from overall network dynamics, not a "specifically tailored" gain function), and much data indeed indicate nonabrubt onsets and offsets of motor command cells (e.g., the "phasic MT" cells in motor cortex of Kalaska, Cohen, Hyde, & Prud'homme, 1989).

In the final chapter of part II, Judy Franklin and Oliver Selfridge make the case that "many of the assumptions made by control theory should be questioned, if our robots are to handle the tasks we should like them to" (p. 349). They go on to sketch possible components of an ambitious research program aimed at helping take control theory from its stability-dominated, fixed-goal past to a robotic future where the basic paradigm is adaptive, nonlinear, and robust. They argue that developing such a futuristic control theory depends on "not invariably requiring mathematical justifications of our models" and "opening far wider the doors of what is to be considered control" (p. 351). Echoing a theme from Barto's chapter, they treat this relaxation of mathematical rigor as analogous to the abandonment (by most computer scientists) of program provability as a prerequisite to practical employment of computer programs. They foresee advanced robots as composites of nonprovably correct conventional programs and neural networks, with the latter envisioned ". . . primarily as adaptive modules in larger systems" (p. 355).

Part III of the book comprises three chapters on application domains and the technical challenges they present to neural network theorists. Arthur Sanderson starts this treatment in chapter 15, focusing on the technical demands of automated assembly tasks and stressing the need to understand how parameters such as velocity and tolerable contact forces can be adaptively matched to the requirements of particular assembly tasks. He also points out the need to learn to control "newer systems that incorporate lightweight, flexible arms" whose kinematics and dynamics are much different from traditional massive, rigid arms. Like Mel, Sanderson emphasizes the importance of integrating newer technology that provides, in principle, a basis for much richer use of real-time sensory data in motor control.

In chapter 16, Lyle Ungar discusses the use of neural networks for chemical process control. Ungar notes that chemical processes are ideal for testing neural network techniques as they are often highly nonlinear and difficult to control and have been widely studied vis-a-vis conventional controllers. Ungar also reiterates a theme from Williams' chapter when describing difficulties inherent in chemical process control:

> Delays in response mean that the system is not invertible. They also create a temporal credit assignment problem: it is not trivial to determine which results should be credited to a given action. (p. 392)

A simple chemical control benchmark, the bioreactor problem, is outlined and an implementation using a neural network controller is discussed.

Charles Jorgenson and C. Schley describe in chapter 17 a potential "life and death" application of neural networks: expanding the envelope of conditions under which automatic aircraft landing systems are reliable. Equations describing airframe motion and elementary control subsystems such as pitch autopilot are given in sufficient detail to allow simulations. Though encouraged by the results of preliminary simulations, the authors conclude with a call for faster converging networks and better facilities for incorporating *a priori* knowledge. Several avenues for future research (such as modifying the simulation to copy a human controller) are also suggested to help lead to realization of more robust automatic landing systems.

Chapter 18, written by Martin Herman, James Albus (originator of the CMAC), and Tsai-Hong Hong describes an approach which integrates concepts of artificial intelligence (AI) with modern control theory developed for the Multiple Autonomous Undersea Vehicles (MAUV) project carried out by the National Institute of Standards and Technology. This was an ambitious robotics project that incorporated a full range of the perceptual, world modeling, planning, evaluation, coordination, and execution functions needed by any autonomous system. The bulk of the chapter outlines this rather complex control scheme. Unfortunately, with the exception of some very vague statements concerning the necessity of real-time performance and learning included in the final two paragraphs of the lengthy chapter, no reference to possible improvements using neural networks is made; furthermore, due to the overwhelmingly AI-oriented nature of the controller, it is unclear if introduction of neural network methods into this control scheme would be favorable or feasible. Given Albus' experience with both standard AI techniques and neural networks, it would have been a valuable addition to have a more explicit statement of how the strengths of these different approaches to synthesizing intelligence might best be combined.

Excepting the introductory chapter by Barto, the most useful contribution of this book may well be the appendix containing several benchmark control problems nicely presented by Charles Anderson and Thomas Miller III. These problems were selected to exemplify difficulties of incomplete system knowledge, nonlinearity, noise, and delays that arise in real control situations. In addition to the truck backer-upper, bioreactor, and autolander problems outlined in chapters 12, 16, and 17, problems of pole balancing, ship steering, and manipulator dynamics are described, as well as two problems developed for the 1988 American Control Conference in Atlanta, GA. Problem relevance, possible extensions, existing results, plant equations necessary for simulations, and variable descriptions are all clearly presented.

This book contains several important contributions. After completing the 500+ page volume, the careful reader will have a good understanding of advantages afforded by the use of neural networks in common control schemes as well as a feel for how neural network control can benefit from more extensively studied traditional control methods. The chapters by Kraft and Campagna, Kawato, Mel, Atkeson, and Reinkensmeyer, and Nguyen and Widrow provide concrete examples of some of the capabilities of neural network control systems. The book also succeeds as a sort of workbook for control using neural networks; chapters by Barto, Werbos, Williams, Narendra, and Shanno constitute a "tool kit" that, when coupled with the benchmark problems in the appendix, provide basic materials which allow the interested reader to extend his/her understanding of this subject matter through experimentation. (It should be noted, however, that successful use of this tool kit will often require the reader to seek out the more thorough articles referenced by the chapters to obtain the technical detail required for actual implementations.) Finally, the extensive ground covered by such diverse work as Mel's MURPHY, Houk et al.'s cerebellar model, and Kawato's model of inverse dynamics successfully conveys the multiformity of current neural network research.

The book has some weaknesses, however. First, the vast majority of neural networks used in these models are homogeneous networks embedded in general control schemes; neural networks are treated primarily as a device for "plugging holes" in the range of competence exhibited by extant control systems (e.g., by providing adaptive nonlinear function approximators). Such networks represent the type II neural network approach described above, but little contact is made with type I schemes. Furthermore, emphasis on networks with a more-than-superficial relationship to biology is minimal. An exception to these complaints is the Adjustable Pattern Generator model of Houk et al.; this model consists of a specialized, heterogeneous network inspired by cerebellar and peri-cerebellar circuitry. Also omitted is an introduction to unsupervised learning networks (e.g., see Grossberg & Kuperstein, 1986; Kohonen, 1984) in the general principles section. Such networks can perform valuable functions in complex control schemes. Because of these omissions, neural networks researchers with a primary interest in brain modeling or the qualitative theory of self-organizing dynamical systems will find the volume less pertinent to their interests.

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