A Survey of Neural Networks Applications in Automatic Control

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Abstract-**This paper is a survey of recent literature in neural networks applications in the field of automatic control. It is now generally accepted in the field that for nonlinear, imperfectly or partially known, and complicated systems, neural networks offer some of the most effective control techniques. In this paper, no attempt has been made to provide mathematical or algorithmic details of the various approaches that are being proposed in the literature; instead, general outlines of some of the techniques have been given. The survey is not presented in a chronological order. It is not an exhaustive survey - but an effort has been made to collect publications from different types of journals. Many authors and groups of authors in the field have numerous publications; for each group, we have cited only one or two representative articles. The goal of this paper is to serve as a resource for new researchers in the field.**

1 Introduction

The field of control systems has gone through some spectacular advances during this century. In recent years, some aspects of control theory and practice have started merging with recent developmets in other fields. Within the last decade, biologically-inspired techniques such as neural networks have developed into some of the newest tools in the controls field. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Neural networks can be used very effectively to model, and hence, to design controllers for complicated nonlinear systems. A trained neural network has the following advantages over classical techniques:

1. Adaptive learning: It has the ability to learn how to perform certain tasks based on the data used for training.

2. Self-organization: It can create its own organization or representation of the information it receives during learning time.

3. Real time operation: It allows parallel computation, and special hardware devices that take advantage of this capability are being designed and manufactured.

4. Fault tolerance via redundant information coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

One of the goals in modern control engineering is to find faster and simpler solutions for highly nonlinear control problems in constrained and uncertain environments. This demand originates from the need for controllers for industrial processes that are characterized by nonlinearities or frequent changes in the operating conditions. Many of these complex control problems can not be solved by conventional linear control methods. It is now well established that artificial neural networks can be used to approximate any continuous nonlinear function to any desired accuracy. Moreover, neural networks have the ability to keep learning during their operation. In many cases an explicit and accurate mathematical model of the

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system under control is very difficult to find. In situations where conventional modeling techniques fail to provide a sufficiently good model, neural networks can usually generate better (closer) models. Neural networks can also be used to detect and identify system failures, and to help store information for decision making - for example, providing the ability to decide when to switch to a different controller among a finite number of controllers.

2 Modeling and Controlling Dynamic Systems with Neural Networks

2.1 Major Sources for This Survey

The four basic tools of neurocontrol can be summarized as:

1. Supervised control
2. Direct inverse control
3. Neural adaptive control
4. Adaptive critic methods.

All these tools have been analyzed and applied to various control problems. In general, over the last fifteen years, there has been a high level of activity in neural network applications for estimation, modeling, and control of dynamic systems. Some of the pioneers in the field are Narendra [1], Werbos [2], McAvoy [3], Lewis [4], and a few others who paved the way for numerous other researchers exploring various techniques for neural modeling and control. Research groups at various centers around the world have been active in neurocontrol research – a few of the well-known groups in the USA are at Yale (Narendra), Georgia Tech (Calise), University of Texas at Arlington (Lewis), NASA Ames Research Center (Jorgensen), etc. Many of the fundamental papers on the topics of neural modeling and control have been published in a few major journals such as the IEEE Transactions on: Automatic Control, Neural Networks, Control Systems Technology, Syst., Man and Cybernetics; also in Neural Networks, Automatica and the International Journal of Control. The reader of this paper will find a number of references taken from these journals. However, with more and more researchers working on many different applications of neural networks, papers are being published in very diverse journals such as the IEEE Journal of Oceanic Engineering [5] and Statistica Sinica [6], etc. In this paper, we focus on some of the most recent work in this field - earlier references can be found cited in those papers. The field is so vigorously active that no survey can be done without some restrictions: we have focused mostly on very recent publications. An earlier survey can be found in [7], published in Automatica in 1992.

2.2 Some Recent Work (and Some Missing Aspects) in the Field

In recent years, there has been tremendous research activity in this field [8]-[25]. It can safely be said that neural-networks-based control has earned its place as one of the most effective methods for uncertain, nonlinear, and some types of time-varying systems. A common thread in many of these papers is a stable controller-parameter adjustment mechanism, which is developed using the Lyapunov theory; most of the network training is performed with some variation of the backpropagation algorithm – using an alpha-modification-type updating law, or other types of elements to improve the training speed and quality. Typically, simulation results showing the feasibility and performance of the proposed technique are given. Among the most popular applications for neural control are robotic manipulators, control of multijoint arm movements, chemical process control, aircraft flight control (autolander), underwater autonomous vehicles, etc. A very useful idea would be to use some specific benchmark problems, apply various competing techniques for controlling them, then carry out a full and thorough comparative study. It appears that this is what is missing at this time, although a set of such benchmark problems is provided in the appendix of the book *Neural Networks for Control* [2], with detailed descriptions of the bioreactor, autolander, pole balancer, steering a tractor-trailer, etc.

A few recent papers have brought out some aspects that are not commonly found in most other papers. For example, in 1997 Rudolph and Kroplin published a paper [26] on modeling assumptions and artificial neural networks. From the principle of dimensional homogeneity, they gave a proof for the Pi-Theorem, which is valid for all dimensionally homogeneous function equations. Several important restrictions, properties and conclusions about the neural network generalization are then proved by the Pi-

Theorem and justified by the principle of dimensional homogeneity. In [27], Rudolph suggested direct and indirect neural network control strategies for non-linear and adaptive control of smart structures. In indirect neural network control the identified plant models are usually implemented as black-box neural networks using no apriori knowledge. According to Rudolph, the generalization and learning properties of neural networks designed using dimensional analysis are superior to conventional black-box networks.

In the numerous papers and many books [2, 28] that have appeared on the topic of neural control or 'modeling and control', almost all of the modeling is done with the ultimate goal of controller design - although sometimes the modeling or system identification phase can be bypassed in order to achieve direct control. In some papers, however, the modeling aspect receives primary attention [29]-[32]; typically, these are parametric models, and these models are later intended to be used for control purposes. Some researchers [34] are investigating non-parametric models and control schemes; this approach may hold even more promise than the parametric approaches. Overall, neural networks have proven to be extremely effective in dyanmic system modeling. In a 1999 paper, Dingankar [35] discusses the "unreasonable effectiveness" of neural network modeling from a fresh perspective. He uses methods from number theory and proves the existence of approximation schemes that converge at a very high rate. However, it appears that there is one missing aspect in all this modeling activity: despite the success and accuracy of neural-networks-based models, almost no attention has been paid to the issue of the quality of the residuals of the modeling process. This is surprising - since one of the fundamental tests of "goodness of fit" is the quality and properties of the residuals. Perahps this gap (that is, lack of attention to the quality of residuals) is primarily due to the fact that most researchers have focused on deterministic systems. A notable exception is Spall [36]. We expect that this gap will be filled by researchers who are exploring the use of neural-networks-models for the purpose of decision-making in fault-detection schemes, since the distribution of the residuals is crucial to successful fault detection. One example of using neural networks to treat residuals of a modeling process is found in Chowdhury [37], where she maps the residuals into a weighted Chi-squared random variable.

Fundamentally, all the neural-networks-based models are variations on the Nonlinear AutoRegressive Moving Average (NARMA) structure. Some researchers are investigating the possibility of converting these NARMA-type input-output models into state-space models, in order to be able to take advantage of the well-established state-space theory and utilize its applications. A 1990 survey of nonlinear modeling with input-output structures can be found in [38]. In a 1999 paper, Kotta and Sadegh [39] proposed two approaches for state space realization of NARMA models. Later, Kotta and Chowdhury investigated the use of the Additive NARMA model, in which the nonlinear structure is preserved but the input-output time-steps are pairwise (and additively) separated. In [40], these authors show that the conventional full NARMA model does not allow state-space realization, but the Additive NARMA model does; they use a neural network to estimate this model in real-time, using a Kalman filtering technique.

3 Conclusions

It can be concluded that in the outstanding problems requiring new control methodologies, neural networks based techniques are becoming more and more applicable. Such applications range from manufacturing automation to autonomous vehicles to flight control, and are best served by combinations of classical and neural tools. Neural modeling, while mainly used for controller design purposes, can also be very effective in the field of detection of faults in dynamic systems. One interesting and important sign of maturity of the field is that in many recent books on nonlinear control, neural techniques are routinely included – even though the title of the book says nothing to indicate this content. In this brief survey paper, we have attempted to provide a baseline for beginning researchers in this field; in addition, we pointed out a few directions where more attention could be focused.

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