NEURAL NETWORK IMPLEMENTATION TO CONTROL SYSTEMS: A SURVEY OF ALGORITHMS AND TECHNIQUES

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ABSTRACT

In the present paper a number of neural network applications which have been proposed in the last twenty years are discussed. Algorithms and techniques developed by different researchers working in the field are also summarized here.

INTRODUCTION

In recent years there is increase in interest shown in the utilization of neural networks for various research fields such as robotics, optimization, linear and non-linear programming, associative memory, image processing, speech and pattern recognition, and computer vision. This is due to the advances in neural training algorithms and also the availability of fast parallel architectures, including very large system integration, electro-optical and dedicated architectures that have made possible extremely fast, relatively low cost microprocessors for implementing these algorithms.

The need to deal with increasingly complex systems, the need to accomplish increasingly demanding design requirements, and the need to control under increased uncertainty have led a number of researchers to a reevaluation of the conventional control methods. The need to control, in a "better way", complex dynamical systems under significant uncertainty made the search of new methods quite active. Neural networks with their massive parallelism and the learning capabilities appear to offer new promising directions toward better understanding and perhaps even solving some of the most difficult control problems. Interest in neural networks has increased in this decade after a period of inactivity following the shortcomings of early neural networks which were published in the late 1960's. The challenge that the control community faces is to find the best way to fully utilize this powerful new tool in control. The present paper discusses a number of neural network applications which have been proposed in recent years. Designs using neural networks ranging from feed-through systems with no feedback, to fully interconnected systems are briefly described. A summary of algorithms and techniques developed by researchers in the field are also discussed here.

NEURAL NETWORKS AND CONTROL SYSTEMS

In this section we will provide an overview of areas that several researchers had developed algorithms and techniques for control dynamical systems utilizing neural networks. Specifically, the use of neural networks for system identification, adaptive control, modeling of chemical processes, optimization, fault detection, and control of robotic manipulators is described in the sequel.

System identification in the time and frequency domains is examined by Narendra [1] and Chu [19]. In [1] Narendra and Papastathy demonstrate that neural networks can be used for identification and control of nonlinear dynamical systems. Static and dynamic back-propagation methods for the adjustment of parameters are applied. Chu, Shoureshi and Tenirio in [19] present two approaches for utilization of neural networks in identification of dynamical systems. First,

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a Hopfield network is used to implement a least-squares estimation for time varying and time invariant systems. The second approach utilizes a set of orthogonal basis function and Fourier analysis to construct a dynamic system in terms of its Fourier coefficients. **Design of neural controllers** to control nonlinear dynamical systems is addressed by several researchers. Specifically, Psaltis and Sideris in [2] use a multilayered neural network composed of feedback and feedforward controllers to control a given plant. They use several learning architectures to train the neural controller in order to provide appropriate inputs to the plant so the desired response is obtained. A year later, Anderson in [4] designs a controller that deals with issues of delayed performance evaluation, learning under uncertainty and the learning of nonlinear functions. The following year, Kraft and Campagna in [20] compare a neural network-based controller with two traditional adaptive controllers, a self-tuning regulator and a Lyapunov-based model reference adaptive controller. Their results indicate that the neural network approach functions well in noise, works for linear and nonlinear systems and can be implemented very efficiently for large-scale systems. The same year, Chen [21] shows that neural networks can be combined with self-tuning control algorithms to control a class of unknown discrete-time nonlinear systems. Via simulation he shows that his proposed self-tuning scheme can deal with a large unknown nonlinearity. Further, Nguyen and Widrow in [23] show how a neural network can be used to solve highly nonlinear control problems. Antsaklis, Passino, and Sartoni in [3] use a neural network called the multilayred perceptron to perform numeric-to-symbolic conversion.

Modeling using neural networks is presented by the following articles: Lippman in [5] presents neural network models that can be used for pattern classification. Two years later, Moody and Darken in [13] propose a network architecture which uses a single internal layer of locally-tuned processing units to learn both classification tasks and real-valued function approximations. The proposed networks learn faster than the ones using back-propagation method. The following year, Bhat, Minderman, McAvoy, and Wang [16] use neural networks for modeling non-linear chemical systems. Specifically, they use back-propagation network to model the system.

The utilization of neural networks for **optimization** purposes is addressed by Bavarian and Rauch in 1988 and Segura in 1989. Specifically, Bavarian in [6] uses two simple examples to illustrate control and optimization with neural network architecture. Rouch, and Winarske in [9] introduce the use of neural network computational algorithms to determine optimal traffic routing for communication networks. Further, Segura , and Burl in [12] design a neural network controller with the ability to learn on line the optimal control law for a crew equipment retriever.

Methods to provide **adaptive control** for nonlinear systems are introduced by the following two papers. Guez, Eilbert, and Kam in [8] propose a computing architecture for adaptive control based on computational features of nonlinear neural networks. Two years later, Goldenthal, and Farrell in [14] propose the use of neural networks in adaptive control loops. Specifically, they present an extension of the back-propagation algorithm which adaptively determines the interconnection parameters necessary for the neural network to function as a closed-loop controller and to force the closed-loop system to match a desired reference response.

The article by Naidu, Zafiriou, and McAvoy [18] addresses the use of the back-propagation neural network for sensor **failure detection** in process control systems.

The main emphasis in the next three articles is the **control of robots** using the learning capabilities of neural networks. Kawato, Uno, Isobe, and Suzuki in [7] based on physiological information and previous madels propose computational theories for the (a) determination of a desired trajectory in the visual coordinates (b) transformation of the trajectory from visual coordinates to body coordiates and and they furtheer introduce a hierarchical neural network model to deal with motor command. The application of this approach to robotics is also outlined. Negata, Sekiguchi, and Asakawa in [22] preaent a mobile robot whose behavior is controlled by a structured hierarchical neural network. Further, a learning algorithm for real-time control is developed , and the "training" of the robot is discussed. The same year, Handelman Lane, and Gelfand in [24] present a methodology for integrating neural networks and knowledge-based systems for the purpose of robotic control, patterning the integration after models of human motor skill acquisition Information about learning algorithms in neuraol networks is given in the next article. Sanner and Akin in [15] develop control algorithms to train neural networks to regulate the pitch attitude of an underwater telerobot.

The **stability** problem of dynamic systems is addressed by Li and Chua. In 1988 Li, Michel, and Porod [10] investigate the dynamic properties of a class of neural networks by studying the qualitative behavior of equiligrium points. Specifically, they obtain results related to the stabillity properties of an equilibrium, asymptotic behavior of solutions. Further, they design a neural network with prespecified equilibrium points which are asymptotically stable. The same year, Chua and Yang in [11] perform an in-depth analysis in the Lyapunov sense, as well as, computeer simulations of the network are performed.

ALGORITHMS

There are at least five algorithms used by researchers to control dynamical systems utilizing neural networks. Specifically, the five algorithms are:

1. Supervised Control /Learning.
2. Inverse Dynamics.
3. Stabilization.
4. Propagation Through Time .
5. Adaptive Critic Systems.

In the sequel we will summarize each of the methods mentioned above.

Supervised Control/Learning

In supervised learning, a neural network is given a set of training inputs X(t) and targets Y(t). To complete the design one needs to determine "H" i.e. design some kind of network to perform supervised learning. Back-propagation is one kind of supervised learning module.

Inverse Dynamics

In inverse dynamics the observed state X(t) of a system is assumed to be a function of current actions u(t) and the prior state if the system:

$$X(t) = F(u(t), X(t-1)) \qquad (1)$$

We do not have to know F but we assume that it is invertible as function of X(t) for any X(t-1). In the training or adaptation phase one is given examples of X(t) which resulted from actual inputs u(t) tried out in some experiment. Supervised learning is used to adapt the network such that

$$u(t) = H(X(t), X(t-1)) \qquad (2)$$

Then in the application phase, given a desired trajectory X*(t) the network H inputs X*(t) and X(t-1) and outputs a control vector u which will lead the system to match the desired trajectory.

Stabilization

Several researchers have worked extensively in the stabilization of dynamic systems utilizing neural networks. There are some promising results in the area but there is space for future work. Standard designs like the self-tuning regulator and model reference adaptive control have been proven to be adequate and stable.

Backpropagation Through Time

Suppose that the model predicts that

$$R(t) = F(R(t-1), u(t))$$

where R(t) is a vector describing the state of reality at time t, u is a vector of controls, and F is implemented by the neural net. Suppose also that there is no random noise in the plant. Further, suppose we try to optimize V(R) which is differentiable over all R(t) for all t.

Using this method one may calculate the derivatives of V with respect to u(t) at all times. By adapting u(t) in response to these derivatives, one obtains the optimal actions or weights.

Adaptive Critic Systems

Adaptive critic systems can be used as in the previous method except that full allowance is made for the presence of noise. This approach requires certain approximations that make it less accurate than backpropagation in time in the case that noise may be neglected.

Since exact use of dynamic programming to optimize the critic in complicated problems is exceedingly complex, the approach is simplified by approximating the functional J(R) as

$$J(R) = \max_{u}[J(F(R,u,w))] + U(R) - U_o$$

where F is represented by a neural network. Several methods may be used to make the above equation approximately true, including, heuristic dynamic programming, dual heuristic programming(DHP) and globalized DHP.

SUMMARY

The use of neural networks in the areas of identification, robotics, detection, adaptive control, modeling, optimization, and robotics has been addressed by several researchers in recent years. In the present paper a survey of articles utilizing neural networks to control linear and nonlinear dynamical systems is provided. A summary of algorithms and techniques used by several researchers working in the field is provided. Further research is needed in all areas mentioned above to fully justify that a powerful tool such as neural networks can be used for analysis and design of complex high order dynamical systems.

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