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Stabilization of Dynamical System Using Artificial Neural Network

A.P. Cheema[1] and Mudit Gupta[2]

[1]GL Bajaj Group of Institutions, Mathura (U.P.)INDIA
[2]Amrapali Group of Institutions, Haldwani, (Uttarakhand), India

ABSTRACT*:* The goal of a present paper is based on the Neural Network controller which is used to make a non-linear system stable while providing improved performance and robustness. This approach is successfully applied to numerous systems. The controller may need to be adjusted slightly when moving from the design model to the actual implementation due to a mismatch between the model and true system. There are also cases when a control system performs well for a particular operating region, but when tested outside that region, performance degrades to unacceptable levels. These issues are addressed by robust control design. In this paper we shall concentrate on the supervised control learning scheme for stabilizing the non-linear system.

Keywords: Artificial Neural Network (ANN), PID, Adaptive Linear Neural Network (ADALINE), RBF (Radial Basis Function),MLP (Multi Layer Perceptron).

I. INTRODUCTION

Typically, control systems are designed so that the plant output follows some reference input while achieving some level of “disturbance rejection.”
In the area of “robust control” the focus is on the development of controllers that can maintain good performance even if we only have a poor model of the plant or if there are some plant parameter variations.
Neural networks are parameterized as nonlinear functions. Their parameters are, for instance, the weights and biases of the network. Adjustment of these parameters results in different shaped nonlinearities. Typically, the adjustment of the neural network parameters is achieved by a gradient descent approach on an error function that measures the difference between the output ofthe neural network and the output of the actual system (function). That is, we try to adjust the neural network to serve as an approximator for an unknown function that we only know by how it specifies output values for the given input values (i.e., the training data). It is important to note, however, that neural networks are not unique in their ability to serve as approximator. There are conventional approximator structures such as polynomials. Moreover, there is the possibility of using a fuzzy system as an approximator structure. Historically, fuzzy controllers have stirred a great deal of excitement in some circles since they allow for the simple inclusion of heuristic knowledge about how to control a plant rather than requiring exact mathematical models. This can sometimes lead to good controller designs in a very short period of time. We will study approximators (neural or fuzzy) that satisfy the “universal approximation property.”
If an approximator utilizes the universal approximation property, then it can approximate any continuous function on a closed and bounded domain with as much accuracy as desired
(However, most often, to get an arbitrarily accurate approximation you have to be willing to increase the size of the approximator structure arbitrarily). It turns out that some approximatorstructures provided much more efficient parameterized nonlinearities in the sense that to get definite improvement in approximation accuracy they only have to grow in size in a, linear fashion.
The practical benefits of neural networks or fuzzy systems are the following:
1. They offer forms of nonlinearities (e.g., the neural network) that are universal approximators (hence more broadly applicable to applications) and that offer reduced ideal approximation error for only a linear increase in the number of parameters.
2. They offer convenient ways to incorporate heuristics on how to initialize the nonlinearity (e.g., the fuzzy system).

II. ADAPTIVE CONTROL TECHNIQUES

In the area, of adaptive control, to reduce the effects of parameter variations, robustness is achieved by adjusting (i.e., adapting) the controller on-line.For instance, an adaptive controller for the cruise control problem would seek to achieve good speed tracking performance even if we do not have a good model of the vehicle and engine dynamics, or if the vehicle dynamics change over time (e.g., via a weight change that results from the addition of cargo, or due to engine degradation over time). At the same time it would try to achieve good disturbance rejection.

Adaptive mechanisms are used within the control laws when certain parameters within the plant dynamics are unknown. An adaptive controller will thus be used to improve the closed-loop system robustness while meeting a set of performance objectives[1]. If the plant uncertainty cannot be expressed in terms of unknown parameters, one may be able to reformulate the problem by expressing the uncertainty in terms of a fuzzy system, neural network, or some other parameterized nonlinearity.

An adaptive controller can be designed so that it estimates some uncertainty within the system, and then automatically designs a controller for the estimated plant uncertainty. In this way the control system uses information gathered on-line to reduce the model uncertainty, that is, to figure out exactly what the plant is at the current time so that good control can be achieved.

1)Direct Adaptive Control: Since there is a direct adjustment of the parameters of the controller without identifying a model of the plant, hence it is called a "direct adaptive control method" [2].

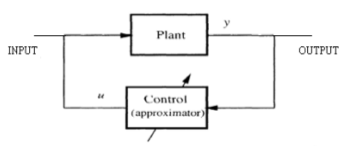

Fig. 1. Direct Adaptive Control.

2)Indirect Adaptive Control: This scheme uses an approximator (often referred to as an "identifier" in the adaptive control literature) that is used to estimate unknown plant parameters and a "certainty equivalence" control scheme in which the plant controller is defined ("designed") assuming that the parameter estimates their true values[3].

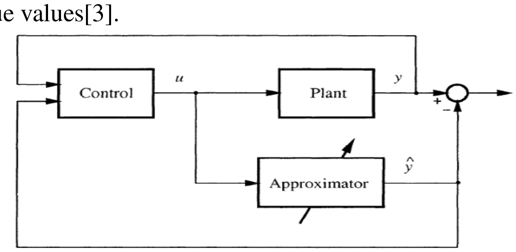

Fig. 2. Indirect Adaptive Control.

Here we will discuss only the direct adaptive control method because it is easier than the indirect adaptive control scheme.

IV. ARTIFICIAL NUERALNETWORK

The basic part of artificial neural network is neuron. Neurons are the fundamental elements in the central nervous system. The following diagram shows the components of a neuron.

It has three main parts- cell body,dendrites and axon. The dendrites receive signals coming from the neighbouring neurons. The dendrites send their signals to the body of the cell. The cell body contains the nucleus of the neuron. If the sum of the received signals is greater than a threshold value, the neuron fires by sending an electrical pulse along the axon to the next neuron. The following model is based on the components of the biological neuron. The inputs X_0-X_3 represent the dendrites. Each input is multiplied by weights W_0-W_3. The output of the neuron model, Y is a function, F of the summation of the input signals[5].

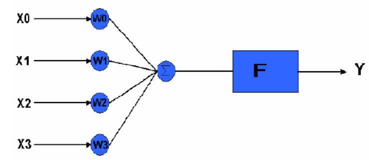

Fig. 3. Diagram of the neuron model.

Neural networks have three main modes of operation- supervised, reninforced and unsupervised modes of learning[6]. In supervised learning the output from the neural network is compared with a set of targets , the error signal is used to update the weights in the neural network[7]. Reinforced learning is similar to supervised learning however there are no target given. Unsupervised learning updates the weights by using the input data only.

There are three main types of activation function- tan-sigmoid , log-sigmoid and linear[8].

Different activation functions affects the performance of an ANN.

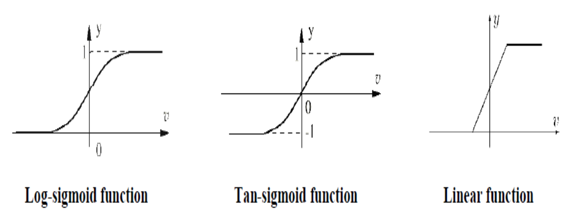

Fig. 4. Activation Function.

In this paper the Direct Adaptive neural network is used for supervised learning of Inverted Pendulum system which is a non-linear system.

V. NEURAL CONTROL OF THE NON-LINEAR SYSTEM

The main task of this work is to design a controller which keeps the pendulum system inverted[11]. There are a few important points to remember when designing a controller for the inverted pendulum. The inverted pendulum is open-loop unstable , non-linear and a multi-output system.These features are described below:-

Open-loop unstable system: Since, the inverted pendulum is an open-loop unstable system.Hence, as soon as the system is simulated the pendulum falls over. Neural ntworks take time to train so the pendulum system will have to be stabilized.

Nonlinear system: Linear PID controllers cannot be used for this system because they cannot control the complicated non-linearities in the pendulum system. ANN's have shown that they are capable of identifying complex nonlinear systems.

Multi-output system: The inverted pendulum has four outputs, in order to have fullstate feedback control of the system, four PID controllers would have to be used. But only one ANN could be used instead of four PID's because of the parallel nature of NN. This is the main benefit of using ANN instead of PID controller.

A. Supervised Control

It is so called because it is possible to teach a neural network the correct actions by using an existing controller or human feedback. Most traditional controllers (feedback linearisation based control) are based around an operating point. This means that the controller can operate correctly if the process/plant operates around a certain point. But if there is any type of uncertainty or change in the unknown plant these controllers will fail. The advantages of neuro-control is if an uncertainty in the plant occurs the ANN will be able to adapt it's parameters and maintain controlling the plant when other robust controllers would fail.

In supervised control, correct actions are provided for the neural network to learn. In offline training the targets are provided by an existing controller, the neural network adjusts its weights until the output from the ANN is similar to the controller[9].The controller calculates the correct magnitude and force to keep the pendulum stable.

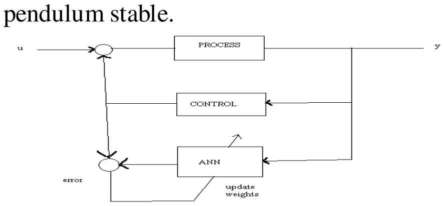

Fig. 5. Supervised learning using an existing controller.

The problem of controlling the non-linearities, is solved by using an adaptive neural toolbox which is an add-on for simulink[10].This toolbox basically allows for online neural learning to occur. The block diagram of the toolbox is shown below. This toolbox contains an ADALINE(Adaptive Linear) NN, RBF (Radial Basis Function),MLP (Multi Layer Perceptron) simulink blocks.

There is an interface for each block so that the user can set the network parameters such as learning rate , number of the neurons in each layer, etc. All of the blocks have the same interface so its possible to try out many different networks quickly and easily.

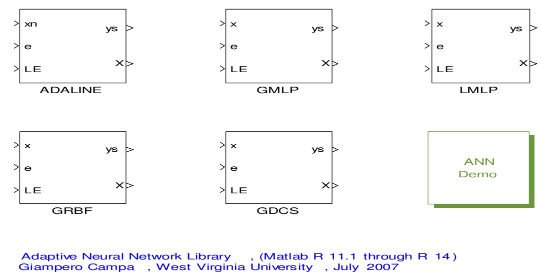

Fig. 6. Adaptive Neural Network Toolbox.

The inputs to each blocks are:

x: The input vector to the neural network.

e: The error between the real output and the network approximation.

LE: A logic signal that enables or disables the learning.

The outputs of each block are:

Ys: The value of the approximate function.

X: All the "states" of the network, namely the weights and all the parameters that change during the learning process.

There is an interface for each block so that the user can set the network parameters such as learning rate , number of the neurons in each layer, etc.

VI. CONCLUSION

We have only concentrated on the supervised control learning scheme.It concluded that the supervised control technique is the most efficient method to implement and to make the system stable if the system is non-linear. The next possible future research could be on unsupervised control learning scheme of the non-linear system. Supervised control with neural networks has been done many times but unsupervised control is a more difficult but an intresting problem.

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