Journal of the Korea Academia-Industrial cooperation Society
Vol. 14, No. 12 pp. 6484-6487, 2013

http://dx.doi.org/10.5762/KAIS.2013.14.12.6484

Direct Controller for Nonlinear System Using a Neural Network

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신경망을 이용한 비선형 시스템의 직접 제어

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Abstract This paper reports the direct controller for nonlinear plants using a neural network. The controller was composed of an approximate controller and a neural network auxiliary controller. The approximate controller provides rough control and the neural network controller gives the complementary signal to further reduce the output tracking error. This method does not place too much restriction on the type of nonlinear plant to be controlled. In this method, a RBF neural network was trained and the system showed stable performance for the inputs it has been trained for. The simulation results showed that it was quite effective and could realize satisfactory control of the nonlinear system.

요 약 본 논문은 비선형 동적 신경망을 이용한 직접 제어에 관한 연구이다. 제어기는 근사화 제어와 신경망 보조 제어 입력으로 구성되어 있다. 신경망 제어 입력은 출력 추적 오차를 더 줄이기 위해 보완 신호를 제공한다. 이 방법은 제어할 비선형 시스템의 종류에 많은 제한을 두지 않기 때문에 RBF 신경망을 이용하여 입력에 대해 안정적인 성능을 가지고 있다. 시뮬레이션 결과는 매우 효과적이며 비선형 시스템의 만족스러운 학습 성능을 증명하였다.

Key Words : complementary signal, direct controller, neural network, nonlinear system, RBF

1. Introduction

The conventional design methods of a control system often require the construction of a mathematical model describing the dynamic behavior of the plant to be controlled. When such a mathematical model is difficult to obtain due to uncertainty or complexity of systems, these conventional techniques based on a mathematical model are not well suited for dealing with. Artificial neural network techniques have been suggested for identification and control of nonlinear plants for which conventional techniques of control do not give satisfactory performance, such as the accuracy in matching the behavior of the physical system.

A good method of applying neural networks for control must have the following properties:

1. It must be applicable to nonlinear plants, since there are already good methods of control for linear plants.
2. It should not put too much restriction on the type of nonlinearity that it can handle.
3. It is preferable to have an Unsupervised Learning method for the neural network because the desired output form of a system for a given input may be known, but the input form of a plant that produces that desired output is not generally known. Unsupervised Training can avoid identification of the plant or its inverse model, which is generally not easy to obtain.
4. The system should be stable at least for the class of inputs it has been trained for.
5. In most cases open loop performance of a plant can

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Received September 30, 2013 Revised October 21, 2013 Accepted December 5, 2013

be observed and a approximate controller can be devised for that. It would be desirable if we could put as much knowledge as possible in the design of this controller and only leave the extra fine tuning to the neural network controller.

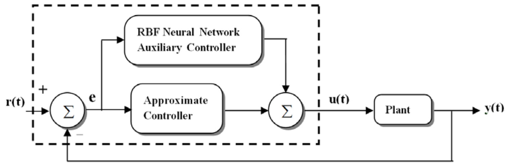
According to the above requirements, a direct auxiliary controller for nonlinear plants using neural network is presented.

2. Controller Design

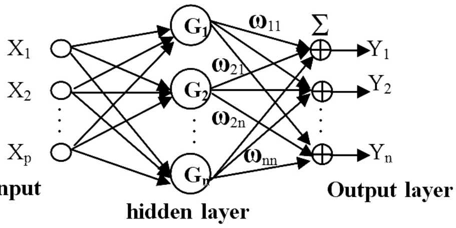
The controller presented here is composed of an approximate controller and a neural network auxiliary controller. The structure of controller is shown in figure 1. The approximate controller gives the approximate performance and the neural network auxiliary controller is used for the purpose of further fine tuning.

The approximate controller can be a PID or any other conventional controller. It can be designed by using the known dynamics of nonlinear plant. The neural network employed in this scheme is an Radial Basis Function Network (RBFN). It produces the complementary signal to further reduce the error e between output y and the reference input r. The structure of RBFN is showed in Figure 2. It is a network with two layers, a hidden layer of radial basis neurons and an output layer of linear neurons. A common choice for the basis function is a Gaussian given by the (1).

Where Ci represents the center of the basis function and σ denotes its width. The norm ||•|| in equation can be expressed by Euclidean distance. The weights and biases of each neuron in the hidden layer define the position and width of a radial basis function. Each linear output neuron forms a weighted sum of these radial basis functions. With the correct weight and bias values for each layer, and enough hidden neurons, a RBFN can fit any function with any desired accuracy. The advantage of the RBFN is its rapid learning, generality and simplicity. RBFN finds the input to output map using local approximations. It can be trained faster than BP and have none of BP's training problems such as saturation and local minima.



[Fig. 1] The structure of the controller



[Fig. 2] Radial Basis Function Network

In the RBFN training stage we first observe the performance of the system with the approximate controller for a certain period of time and measure the range of error between the output of the plant and desired output. Then we divide this error span into certain sections and for each section we perform a perturbation test: We increased the input to the plant by δe whenever total square error between the output of the plant and desired output falls within a specified region. If this change of the input results in a lower value of the total square error, we modify the output weight of the neural network controller to work accordingly. This action is continued for all sections and the whole process is repeated until no modification can reduce the error.

Taking an overlapping Gaussian activation function for kernel units supposedly provides a smoother response and better generalization. But in our case the amount of interference was so high and we obtained a better performance with non-overlapping regions. Nevertheless, smoothness of the output can be enhanced by dividing the correction for each section by modifying the cost function used for training from J=∑e2 to J=∑(enew2+k(enew -eold)2) for k<1.

During the training stage, each time only one kernel unit responds and one weight is adjusted, This results in a shorter training time compared with Multi-layer Perception (MLP) type networks. Since weights are adjusted by a small value δ each time, the number of necessary iterations depends on the size of error or the accuracy of the approximate controller.

The point that makes this method different is the way in obtaining the necessary corrections, which is based on the effect of weight perturbation on the total square error for a certain period of time. Perturbing the weights of a network is used in Madaline Rule III (MR III) training for analog implementation of neural networks. Because this method does not need prior knowledge about the transfer characteristics of the computing devices, it is not affected by the effects of neuron to neuron variations. Training the network based on its instantaneous result of the error will cause instability when used in a feedback loop. The performance of the system here is observed for a certain period of time and if any adjustment for any given amount of error increases the total square error, it would not be accepted. This proves the stability of the system for the class of inputs it has been trained for.

Generally optimization methods based on parameter perturbation are bound to failure when many parameters are involved in perturbation and that is because of the moving target effect of the other parameters. It is not the case in the proposed system for which only one or few related parameters are active at each time. At present, methods for directly adjusting the control parameters based on the output error are not available. The work presented in this paper is a step toward direct adaptive control.

3. Simulation Study

Different nonlinear systems were considered to evaluate the effect of the proposed method. Figure 3 gives the effect of controller when it is used for three different nonlinear plants. In this figure, y(.) denotes the plant output without controller, ym(.) denotes the desired output, r(.) denotes the reference input and yc(.) denotes the output of the plant with controller. An RBF type network with 30 kernel units each sensitive to different ranges of error were used. Input weights and activation function of the units were fixed. Output weights were perturbed and adjusted according to the effect of perturbation on the total square error for 400 sampling time. For a sinusoidal input (r(k)=sin(k/50)) and perturbation amount of δ=0.1, the amount of reduction in aggregated square error for a full cycle of input is example 1:from 3.69 to 1.33, example 2:from 105.84 to 26.44 and example 3:from 32.11 to 4.56. To observe the learning and generalization capability of the system, the controller was trained on a step response and its performance was observed on the sinusoidal input. Training the network with different types of input will enhance the generalization capability of the system.

Example 1

$$\begin{cases} y(k) = \dfrac{1.2y(k-1)}{1+y(k-1)^2} + 0.5u(k-1) \\ y_m(k) = 0.3y_m(k-1) + 0.2y_m(k-2) + 0.5r(k-1) \end{cases}$$

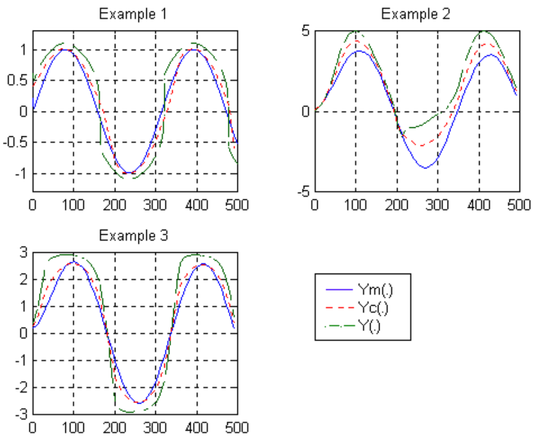
Example 2

$$\begin{cases} y(k) = \dfrac{y(k-1)y(k-2)(y(k-1)+2.5)}{1.3+y(k-1)^2+y(k-2)^2} + 1.5u(k-1) \\ y_m(k) = 0.7y_m(k-1) + 0.1y_m(k-2) + r(k-1) \end{cases}$$

Example 3

$$\begin{cases} y(k) = sat(0.5y(k-1) + 0.2y(k-2) + 2.1u(k-1)) \\ y_m(k) = 0.48y_m(k-1) + 0.2y_m(k-2) + r(k-1) \end{cases}$$

$$(sat(x) \equiv -3 + \frac{6}{1+\exp(-x)})$$



[Fig. 3] Ym(.) is the output of the reference model, Y(.) is the output of system without NNC and Yc(.) is the output of system without NNC in the example1,2 and 3.

4. Conclusions

A neural network controller for nonlinear plants is used in combination with an existing conventional controller, which removes the need for a generalized training scheme. The controller is guaranteed to perform stably for the class of inputs that it has been trained for. Using this method of control does not require assumption of a model for the plant and it makes it different from conventional control methodologies. Furthermore, since training of this network does not require backpropagation of error, it makes direct adaptive control possible, a structure beyond the capabilities of backpropagation based on neural networks. The structure used here can be view as a fuzzy controller implementation for which the control actions or rules which depend on the error between the plant output and the desired output are deduced in training time. It can also be viewed as a gain scheduling adaptive controller which can work for any unknown plant with no attempt to linearize the system at each region.

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<Research Interests>
Image processing, Signal process