SYSTEM IDENTIFICATION IN HYDRAULIC SERVO SYSTEM WITH DIAGONAL RECURRENT NEURAL NETWORKS

Chen ping Qiu lihua
Electrical & Mechanical Engineering
College of automation science and electric engineering
Beijing University of Aeronautics and Astronautics
100083 Beijing P.R.China Email: chen_ping_2000@263.net

ABSTRACT

This paper points out that the Diagonal Recurrent Neural Networks (DRNN) can deal with the dynamical system more effectively. We use this neural networks to identify the hydraulic servo system dynamical performance .The adjustment of weight is the algorithm that take time varied into account. The simulation results and experiments testified that this method could rapidly and exactly get the dynamical performance.

Key words Hydraulic servo system
Diagonal Recurrent Neural Networks (DRNN)
System identification

0 INTRODUCTION

Hydraulic servo system is a complicated system with the components of mechanic, electric and hydraulic. There are many nonlinear and uncertain factors such as nonlinear gain cipher error lag load disturb energy undulate medium variety etc. Though conventional methods can establish mathematics model of hydraulic servo system with relatively self-contained expression, we often encounter some difficulties when applying the mathematics expression in practice. It's inevitable because the expression is deduced by physics law of the system, we can't count all infect factors into it. If we count more factors in, the complexity of this model will be highly increased, so it is difficult to apply. This is very important in practice that model of hydraulic servo-system to be established, this step is necessary for thoroughly analysis system and control and fault diagnosis. Neural network can establish model of hydraulic servo-system by learning the mapping relationship of practical system input and output data. So we can get the neural network model instead of mathematics model, in this way we can avoid the errors caused by the inaccurately in establishing mathematics model, and we can construct more precise system in making control system and fault diagnosis.

1 Diagonal Recurrent Neural Networks and the capability of nonlinear dynamic mapping

When applying neural network in system identification, the first thing we concerned is the architecture of the neural network, and the pivotal step is to decide the input vector of the neural network. This is just like the confirmation of the order of the linear system. After obtain the order of system most people used the feed forward neural network (FNN), combine with tapped delays (TDL), and the back propagation training algorithm to solve the system identification problem. If the order of model is unknown, the architecture of the neural network is obtained by many trials from lower order to the higher order based on definite target. As for the nonlinear system, it is very difficult to get the order of model, and only can get the approximate architecture by trial and error. The more complicated problem is that many parameters and the construction are mutative during system running period, even varied rapidly. Such as load varied shapely in hydraulic force servo system, pressure pulse in the hydraulic pipe. Though neural network has robust and generalization abilities, for the large change of system construction or parameter, the neural network with fixed construction is difficult to meet the demand of the system identification. A method that is brought up by some people is real-time regulating the structure of neural network, just as Self-Organizing Feature Map network, Adaptive Resonance Theory network and Counter Propagation network. But the structure and algorithm of this kind of network are more complicated, and also it took much time to regulate the architecture and to weight. So it can't meet the demand of real-time system. On the other hand, recurrent neural networks have important capabilities that are not found in feed forward networks, such as attractor dynamic and the abilities to store information for later use. The particular interest is their ability to deal with time varying input or output through their own natural temporal operation. Thus the recurrent neural network (RNN) is a dynamic mapping and is better suited for dynamical system than the feed forward network with BP algorithm.[1][2][3].

This paper applied Diagonal Recurrent Neural Networks (DRNN) in dynamic modeling hydraulic servo system. Since the DRNN structure was brought up by Chao-chee Ku in IEEE Transaction on Neural Network at 1995, it has attracted many attentions because of its simple structure, rapidly convergence, and ease to implement. So the architecture of DRNN is more simple and small than other neural networks when it applied in system identification.

Considering Fig.1, the architecture of DRNN is a modified model of the fully connected recurrent neural network with one hidden layer, the input layer and the output layer. The hidden layer is comprised of self-recurrent neurons. The input layer and the output layer are comprised of ordinary neurons. The activation function of the hidden layer is Sigmoid function.

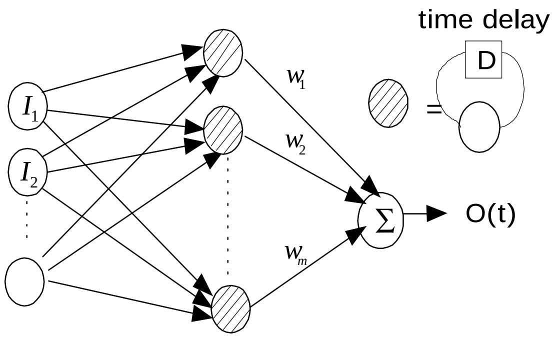

Fig. 1 Structure of the DRNN

In the fig.1, the neuron with shade is the recurrent neuron, where for each discrete time k, $I_i(k)$ is the i th input, $S_j(k)$ is the sum of input to the j th recurrent neuron , $X_j(k)$ is the output of the j th recurrent neuron, $O(k)$ is the output of the network .Depending on the network, W^i W^D and W^O represent input, diagonal, output weight vectors, respectively. The network with this kind of architecture is call diagonal recurrent network. Because W^D is a main diagonal matrix. If N^D£½$\{I^P, H^Q, O^R\}$ represents a DRNN with P inputs Q sigmoid neurons in hidden layer R linear neurons in the output layer. Consider DRNN with P input, Q recurrent one output N^D£½$\{I^P, H^Q, O^1\}$, the mathematical model is described as following:

$$S_j = W_j^D X_j(k-1) + \sum_{i=1}^{p} W_{ij}^I I_i(k) \qquad (1)$$

$$X_j(k) = f(S_j(k)) \qquad (2)$$

$$O(k) = \sum_{j=1}^{q} W_j^O X_j(k) \qquad (3)$$

$f(\bullet)$ is Sigmoid function as commonly applied, and Ambipolar Sigmoid is used in this paper.

As formula (1) (2) (3) described, DRNN have a one-step lag self-feedback neuron in the hidden layer, and the implement dynamic mapping is rely on this feedback.

A generalized algorithm, which is called the dynamic back propagation, is developed to train the network. And the convergence and stability is guaranteed by Lyapuanv function methods, See also [4][5].

2 DRNN MODELING IN HYDRAULIC SERVO SYSTEM

Actual hydraulic system is a complicated nonlinear dynamic system. The target of DRNN modeling research is to implement control and fault diagnosis of hydraulic servo system, so the architecture of DRNNI is decided to apply the target. In this paper the nonlinear system NARMA model is used to represent the hydraulic servo system.

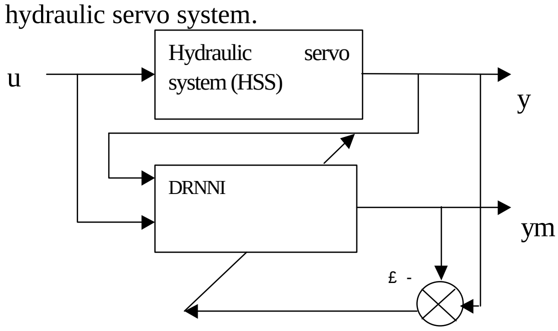

Fig. 2 DRNN identification with serial-parallel architecture

The block diagram of identification system is showed in the figure 2. The serial-parallel identification system is applied in the simulation, which means one of the inputs of DRNNI is the actual system output. On the contrast, in the parallel identification model, one of the input of DRNNI is the output of DRNNI itself. The virtue of this method is guaranteed by the convergence. But the actual system must be connected all the time. Although DRNNI cannot replace HSS and design the controller offline, the serial-parallel identification applied here is advisable for the purpose of DRNN is modeling. The inputs of network are the control value u and actual system output y. Because there is a recurrent neuron in the network hidden layer, the input only need a value of last discrete time, and the information of all past discrete time could be represent in the DRNNI in nature.

The process that DRNNI is used in HSS modeling can be reduce to following steps:

1 Choose control value u and the output of actual system y as the input signals of DRNNI, the neuron number of each layer is decided by trial and error.

2 Initialize weight value and threshold in every layer.

3 Select training sample (or on-line training), input u and y into DRNNI and get the

output y_m,

4 According the error e_m of y and y_m, and according the error function to train the network.

5 Repeat steps of 3 4 above till the precision of identification meet the prearrange demand.

DBP (Dynamic Back Propagation) algorithm used by DRNNI is described as following.

The error function used by DRNNI when weight vector is adjusted, which is showed as following:

$$J_m = \frac{1}{2}(y(\text{k}) - y_m(\text{k}))^2 = \frac{1}{2}e_m^2(\text{k}) \qquad (4)$$

$y(k)$ is the output of actual system, y_m is the output of DRNNI, the gradient of error function J_m relative to weight $W(k)$ is as following:

$$\frac{\partial E_m}{\partial W(k)} = -e_m(k)\frac{\partial y_m(k)}{\partial W(k)} = -e_m(k)\frac{\partial O(k)}{\partial W(k)} \quad (5)$$

The $e_m(k) = y(k) - y_m(k)$ is the error of actual system and DRNNI.

Consider the output layer W^O,

According to formula (1), we can deduce

$$\frac{\partial O(k)}{\partial W_j^O(k)} = X_j(k) \qquad (6)$$

Consider hidden layer, where for each discrete time k, the weight vector is $W(k)$. Considering weight is time varied, we can deduce the gradient as following:

$$\frac{\partial O\text{£¨}k\text{£©}}{\partial W_j^D(k)} = W_j^O(k)\frac{\partial X_j(k)}{\partial W_j^D(k)}$$

$$\text{£½} W_j^O f^{'}(S_j(k))X_j(k-1) \qquad (7)$$

Similar to the above derivation, the gradient of output $O(k)$ and the weight vector of input layer is:

$$\frac{\partial O(k)}{\partial (W_{ij}^I(k))} = W_j^O(k) f^{'}(S_j(k)) I_i(k) \qquad (8)$$

The weights can now be adjusted following a gradient method, the update rule of the weights becomes:

$$W(\text{k}+1) = W(\text{k}) + \text{¦Ç}_I(-\frac{\partial J_m}{\partial W}) \qquad (9)$$

$$= W(\text{k}) + \text{¦Ç}_I\, e_m(\text{k})\frac{\partial y_m(\text{k})}{\partial W} \qquad (10)$$

$$= W(\text{k}) + h_I e_m(\text{k})\frac{\partial O(\text{k})}{\partial W} \qquad (11)$$

Here ¦Ç_I is a learning rate of weight vector W. Take the formula 6 7 8 into formula 11 , the weight adjust algorithm could be reduced.

3 SIMULATION RESULTS

The object of simulation is a hydraulic actuator, which is a representative hydraulic servo system. We can get the nonlinear model by experimentation and theoretic analysis, and then the NARMA model of this system is used in simulation. The architectures of DRNNI and the network are described as above. There are 2 neurons in the input layer, 10 recurrent neurons in the hidden layer, and in output layer is one neuron. Learning rate of weights is 0.3. The values of weight and threshold are random vectors form -1.0 to +1.0. The input signal is a Sin function with 3Hz frequency and with the amplitude of 1.0.

The result of simulation is described in fig.3 ,4.

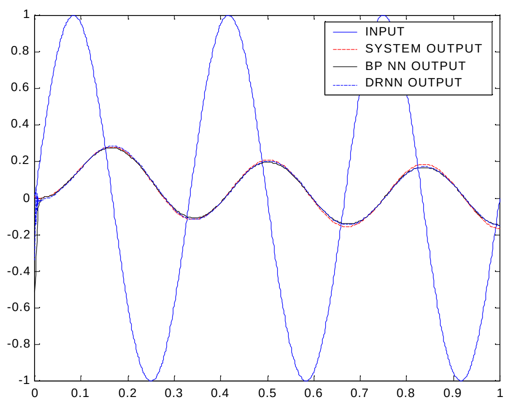

Fig. 3 Result of DRNN Identification

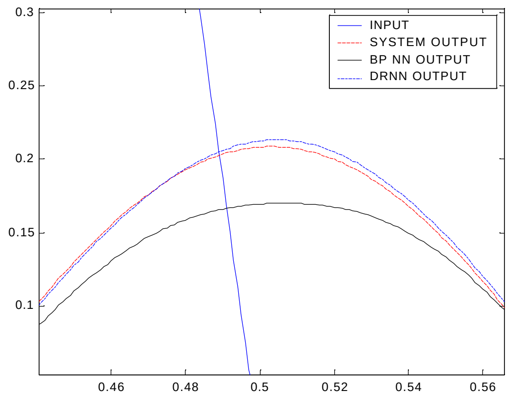

Fig. 4 A part of Fig.3 be Zoomed out

This figure show that the DRNN can catch the dynamic performance more quickly and more precisely than the BP network with the similar structure and initial values. These results show that the method of DRNN identification could rapidly and exactly get the dynamical performance.

4 CONCLUSION

This paper described the diagonal recurrent neural network (DRNN) used in identification of hydraulic servo system. The DRNNI is compared with the feed forward network, the simulation result show that the DRNN model have dynamic mapping characteristics. Moreover, it requires fewer weights when compared with the BP network, so this method could rapidly and exactly get the dynamical performance. The above features allow the DRNN model to be used for on-line application such as control and fault diagnosis in hydraulic system.

REFERENCES

1 Fang chongzhi system identification Tsinghua university press, 1987.(in chinese)
2 Wang Yongji, Tu Jian ,Neural Network Control, mechanic industry press,1998,2.(in Chinese)
3 Zhang Naiyao, Neural Network and Fuzzy Control, Tsinghua university press, 1998,10.(in Chinese)
4 Chao-Chee Ku and Kwang Y. Lee,"Diagonal recurrent neural networks for dynamic system control," *IEEE Tran.Neural networks*, vol.6, No.1, Jan. 1995, pp.144-56. USA.
5 Liang X. and Lee KY. "Comments on "Diagonal recurrent neural networks for dynamic system control". Reproof of theorems 2 and 4 and reply." *IEEE Tran.Neural networks.* vol.8, No.3,May 1997,pp.811-14. Publisher: IEEE USA.
6 Chen wei and Wu jie ,The Correction to the algorithm of Diagonal Recurrent Neural Network, control theory and application,1998,10.(in chinese)
7 Chen wei and wu jie, Modelling of ASVG by using Diagonal recurrent neural network. Automation of Electric Power System, 1999,2.(in Chinese).
8 Lu Jin,Xu Wenli and Han Zengjin,Research on Parallel Identification Algorithm of Neural Networks 1998 5,Volume 15.(in Chinese)