Research on Neural Networks based Modelling and Control of Electrohydraulic System

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Abstract—**The electrohydraulic servo system of a certain type of mines weeping plough is a complex and nonlinear system. It is difficult to construct its accurate model by first principle method and to achieve satisfactory control performance by traditional PID controller. In this paper, the radial basis function neural network with orthogonal least square learning algorithm is used to model the electrohydraulic system and the neural network based direct inverse is adopted to control the system. The experimental results and comparisons with other techniques clearly show the validity of the proposed methods.**

Keywords-electrohydraulic system; neural network; modelling; direct inverse control

I. Introduction

The mechanical subsystem of a certain comprehensive mine sweeping tank is a mine sweeping plough. In the process of mine sweeping operation, the plough will be lowered underground and pushed in front of the tank, so that any mines it encountered are lifted off to the sides, thus a safe route with the whole width of the plough can be cleared. In order to clean the mines thoroughly, the cutting depth should be controlled effectively; however the existing manual control method can't satisfy the tactical requirement of constant cutting depth.

The electrohydraulic position servo system is adopted to control the cutting depth of the plough. In order to keep the cutting depth constant, the electrohydraulic servo system should be controlled and modeled. However, the electrohydraulic servo system inherently has many nonlinear characteristics, such as liquid compress, electro-magnetic transform and friction. Therefore the transfer functions or the state space equations which are obtained from the traditional methods may not perform the idiosyncrasy exactly [1] .In addition, it is difficult to achieve satisfactory dynamic and static performance since these obtained linear models can not represent the highly nonlinear characteristics and uncertainties of the system.

Neural networks have been widely used in many fields due to their abilities in nonlinear mapping and self learning. In the recent decades, great attention has been focused on modeling and control of the electrohydraulic servo system based on neural networks. Liu[2], Ye[3] and He[4] set up the models for electrohydraulic servo systems using multi layer perceptron neural networks or recurrent neural networks, and made the conclusion that the accuracy of the neural networks is better than that of the linear models. Tong [5] proposed a method of neural network based adaptive control for an electrohydraulic servo system with complex nonlinearities and uncertainties. Kang [6] gave a model following adaptive control based on neural network for electrohydraulic servo system subjected to varied load. The proposed control method utilized multiple neural networks including a neural network controller, a neural network emulator and a neural tuner. All these researches mentioned above show that neural networks used in modeling and control of the electrohydraulic servo system could improve modeling accuracy and control performance.

In modeling of complex systems, the most commonly used neural networks are the Back Propagation neural network (BPNN) and the Radial Basis Function neural network (RBFNN). Nevertheless the BPNN has many disadvantages: minimal convergence behavior, slow convergence speed and sensitivity to random initialization. Compared with the BPNN, the RBFNN possess some advantages including higher learning speed, simpler architecture and more powerful ability to approximate functions, thus the RBFNN is more widely used in different areas recently.

Neural networks can be used for modeling and control of complex systems with measurement noise and external disturbance due to their adaptive characteristics. Among various neural network based control techniques, the direct inverse neural network control is simple and practical, thus it is wildly used in control of various complicated systems.

This paper focuses on the modeling and control of the electrohydraulic servo system of a certain mine sweeping plough. The RBFNN is used for modeling and the direct neural network inverse control. The paper outline is listed as follows. Section 2 introduces the structure and principle of the electrohydraulic servo system of the mine sweeping plough. Section 3 details the approaches of neural networks based modeling and control. In section 4, the proposed approaches are applied to the electrohydraulic system, and the experiment results are analyzed. Finally, section 5 gives the conclusions and future work.

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II. THE ELECTROHYDRAULIC SYSTEM OF THE MINE SWEEPING PLOUGH

The electrohydraulic system of a certain mine sweeping plough is composed of servo valve, hydraulic cylinder, imitated boot, rotation angle sensor and plough, as illustrated in Figure 1. When the mine sweeping plough moves forward, the shape of rugged landform can be detected by the imitated boot, and the corresponding signal is generated by the rotation angle sensor, thus the cutting depth of the plough can be calculated. The control signal of servo valve can be computed according to the deviation between the actual depth and the predefined depth value. The obtained signal then drives the servo valve to control the hydraulic cylinder automatically to adjust the cutting depth of the plough [7]. Figure 2 shows the framework of this system, and it can be seen that the system is a typical electrohydraulic position servo system. In the system, there is fixed single input single output function mapping relationship among position displacement of the hydraulic cylinder, angular displacement of the rotation angle sensor and cutting depth of the plough. The function is decided by actual physical size of the system. So in this paper the input signal is selected as the voltage signal of the servo valve, and the output signal is selected as the position displacement signal of the hydraulic cylinder.

In order to motivate the electrohydraulic system sufficiently and obtain complete data containing all its dynamic characteristics, it is important to select an appropriate input signal. In the field of linear system identification, the Pseudo-Random Binary Signal (PRBS) that only contains two amplitude levels is widely used. However, the identifiability will be lost for the nonlinear electrohydraulic using PRBS. So an input signal that contains all interesting amplitudes and frequencies and all their combinations should be employed, such as Pseudo-Random Multi-Level Signals (PRMS), chirp signals, and independent sequences with a Gaussian or uniform distribution. Experience shows that the PRMS is the most suitable choice of input signal for identification of hydraulic system [8]. So in this paper the PRMS is selected as the input signal for the electrohydraulic.

Let v(k) be a white noise. A PRMS is obtained by keeping the same amplitude value for Ns steps:

$$u(k)=v\left[\operatorname{int}\left(\frac{k-1}{N_s}\right)+1\right]\quad k=1,2,\cdots \tag{1}$$

where int(x) is the integer part of x.

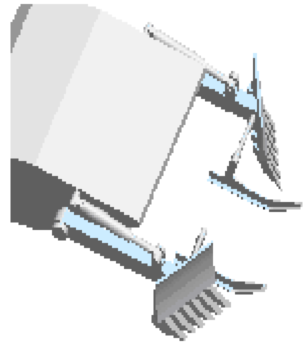

Figure 1. The diagram of the mine sweeping system

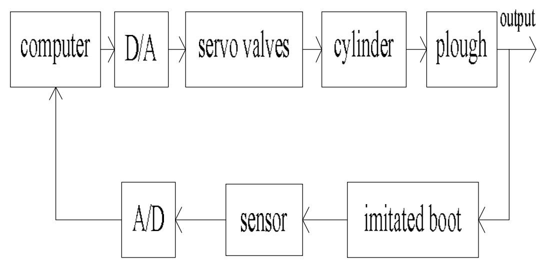

Figure 2. The block diagram of the electrohydraulic system

A generalization of this signal is generated by introducing an additional random variable for deciding when to change the amplitude level:

$$u(k)=\begin{cases} u(k) & \text{with probability } \alpha \\ u(k-1) & \text{with probability } 1-\alpha \end{cases} \tag{2}$$

It is clear that if a is chosen to unity, the input will remain constant over long intervals and hence be of low-frequency character. In practice, the values of Ns and a should be determined reiteratively to motivate the system sufficiently.

In the electrohydraulic system of the mine sweeping plough, the input signal is the control voltage of servo valve in the range of [-8 8] volt, and the output signal is the displacement of the piston in the range of [0 0.45] meter. Although the hydraulic system is a high-order nonlinear system, it will not be vibrated within the normal input allowed. So the experiment to gather data is conducted without any closed loop controller. With 100ms sampling time, 10000 data are collected, as illustrated in Figure 3: (a) presents the input data, and (b) shows the output data.

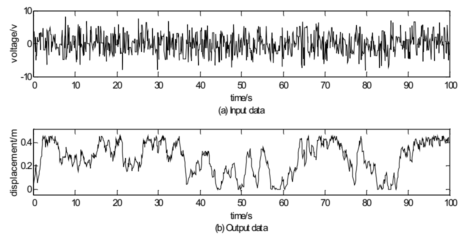

Figure 3. Input-output electrohydraulic system

III. RBF NEURAL NETWORK: MODELLING AND CONTROL

A. RBF neural networks

The radial basis function neural network is a three-layer feedforward neural network which consists of input layer, signal hidden layer and output layer, as depicted in Figure 4. The input layer consists of neurons which corresponding to the elements of input vector. These neurons does not process the input information, they only distribute the input vector to the hidden layer. The hidden layer does all the important process. Each neuron of the hidden layer employs a radial basis function as nonlinear transfer function to operate the received input vector and emits the output value to the output layer. The output layer implements a linear weighted sum of the hidden neurons and yields the output value.

A typical radial basis function that is used in this paper is the Gaussian function which assumes the form

$$\phi_m(x) = e^{-\frac{\|x-c_m\|^2}{\sigma_m^2}}$$

where x is input vector, c_m is the center of RBFNN, $\|x-c_m\|$ denotes the distance between x and c_m, σ is the width.

The output of the RBFNN has the following form

$$y_t(x) = \sum_{m=1}^{M} w_{tm}\phi_m(x) + b_t$$

where M is the number of independent basis functions, w_{tm} is the weight associated with the mth neuron in the hidden layer and the tth neuron in the output layer, b_t is the bias of the tth neuron.

The K-means clustering algorithm and the orthogonal least square (OLS) algorithm are the two widely used techniques for training of the RBF neural networks. For the clustering method, the randomly selected initial centers influence the performances of the RBF neural networks seriously, so the OLS algorithm is utilized to learn the parameters of RBFNN in this paper.

The task of learning procedure is to optimize the RBFNN with appreciate hidden units and parameters base on the measured input and output data. The hidden nodes of RBFNN are selected from training exemplars and it is a problem of subset model selection. The details of the OLS learning algorithm can be obtained in reference [9].

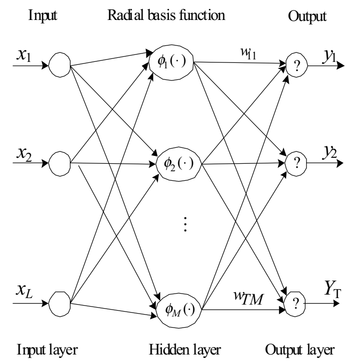

Figure 4. Radial basis function neural

B. The direct neural network inverse control

The direct neural network inverse control combines the idea of the direct inverse control and neural networks, which possesses the advantages of two techniques and improves the control performance.

The direct neural network inverse control is also called the direct self-tuning control of neural networks, in which the identified neural network is used as the controller for the system. Figure 5 illustrates the diagram of the principle of the direct inverse control.

The control performance depends on the modeling accuracy of the inverse neural network. Therefore, the construction of the inverse model plays an important role in the direct inverse control of neural network. In this paper, the combination of generalized training and specialized training technique is used to learn the inverse neural network [10].

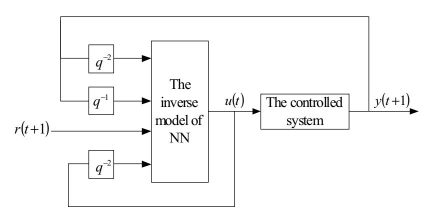

Figure 5. Direct neural network inverse

IV. EXPERIMENTS AND RESULTS

This section presents the application of the neural networks for modelling and control of the electrohydraulic system of a certain type of mine sweeping plough.

For the collected 1000 measured data, the first 600 data are used to train the neural network, while the other 400 data are employed to validate the obtained model.

In order to accelerate the speed of convergence and improve the effectiveness of the OLS algorithm, the collected data are scaled between zero and one

$$x_i^{scal} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}},$$

where x_i, $x_{\max}$ and $x_{\min}$ are the original, the maximum and the minimum values respectively, x_i^{scal} is the value which has been pre-processed.

In order to weigh the performance of the obtained neural networks, the Root Mean Square Error (*RMSE*) is applied to measure the precision of the obtained model

$$RMS(y, y_m) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y(i) - y_m(i))^2},$$

where y is the target value of displacement, y_m is the output of the obtained model, N is the number of data.

Figure 6 shows the comparisons of the output values between the measured output and neural network output. The RMSE of training data and test data are 0.0426 and 0.0475 respectively. It can be seen that the predicted outputs of RBFNN follow reasonably close to the target outputs for both training data and testing data.

In order to show the performance of the direct neural network inverse control efficiently, the comparison is made between the direct neural network inverse control and the conventional PID controller [11]. The parameters of PID controller are tuned as follows: proportional coefficient K_p=8, differential time K_d=0.8 and integration time K_i=5. For experiment, the step signal and the sinusoidal signal are chosen as the reference signal, which are $u_1(t)$=0.4 and $u_2(t)$=0.2sin(0.2πt), respectively.

Figure 7 shows the system response for the step input signal. The performance of the PID and direct neural network inverse control is concluded in Tab.1, which indicates that the direct neural network inverse control is superior to the PID for step input signal.

Figure 8 and Figure 9 show the response of the two controllers for the sinusoidal input signal, respectively. Obviously, the delay of the direct neural network inverse controller is much smaller than that of the PID. So we can make the conclusion that the direct neural network inverse control is better than the PID for the electrohydraulic servo system of a certain mine sweeping plough.

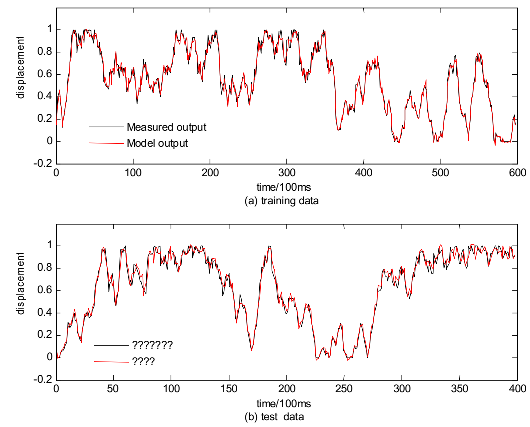

Figure 6. Comparison of measured output

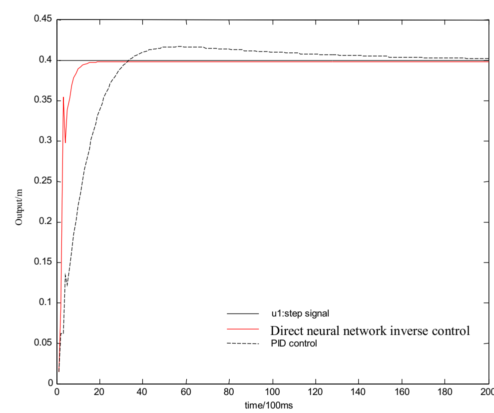

Figure 7. Comparison of direct inverse control and PID for step signal

TABLE I

Tab.1. Performance comparisons of the direct neural network inverse control and the PID control

Indices	***the direct neural network inverse control***	***the conventional PID***
Peak time	2.3s	5.7s
Overshoot	0%	3.6%
Steady-state error	0.45%	0.85%

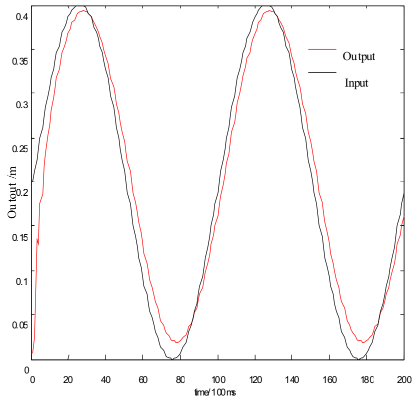

Figure 8. Output response of the direct neural network inverse control

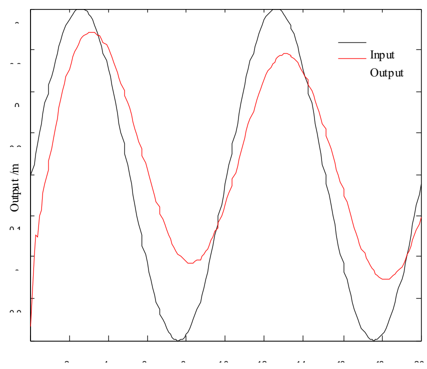

Figure 9. Output response of the PID

V. CONCLUSIONS

The RBF neural network with OLS learning algorithm is employed to model the electrohydraulic system of a certain mine sweeping plough. And the direct neural network inverse control is designed to control the system after obtained the accurate model. The experimental simulation results and comparisons with the other methods show the validity of the adopted techniques.

The further work includes two aspects. Firstly, how to construct more precise and accurate RBF neural networks should be developed. Secondly, in order to get higher control performance, more advanced control techniques can be attempted.

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