Identification and Position Control of Marine Helm using Artificial Neural Network

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ABSTRACT

If nonlinearities such as saturation of the amplifier gain and motor torque, gear backlash, and shaft compliances- just to name a few - are considered in the position control system of marine helm, traditional control methods are no longer sufficient to be used to improve the performance of the system. In this paper an alternative approach to traditional control methods - a neural network reference controller - is proposed to establish an adaptive control of the position of the marine helm to achieve the controlled variable at the command position. This neural network controller comprises of two neural networks. One is the plant model network used to identify the nonlinear system and the other the controller network used to control the output to follow the reference model. The experimental results demonstrate that this adaptive neural network reference controller has much better control performance than is obtained with traditional controllers.

Keywords: Neural Network Controller, Identification, Position control system, Nonlinearity, Marine helm

1. INTRODUCTION

Usually, the traditional PID (Proportional-Integral-Derivative) controller can be used to improve the control performance successfully when position system of marine helm is regarded as a linear system. However, in fact, the real system is nonlinear when saturation of the amplifier gain and motor torque, gear backlash, and shaft compliances are considered[1]. Backlash of decelerator gear, for example, is a common nonlinear factor in mechanical connection of the follower system. Owing to restriction on machining accuracy and assembly, backlash is hard to avoid. In additional, this kind of nonlinearity can not be linearized. Therefore, PID control method is not sufficient to deal with nonlinear situation. An alternative approach to traditional control methods - a neural network reference controller - is proposed to establish an adaptive control system for the position of the marine helm to achieve the desired design conditions.

With the development of artificial intelligent technology, neural network control have been applied very successfully in the identification and control of dynamic systems[2] [3][4][5] instead of traditional PID control in order to have much better control performance than is obtained with traditional controllers, such as less maximum overshoot, less settling time, less steady error and so on.

Since the neural network has powerful universal approximation capabilities of the multilayer perceptron, it should be a good choice to identify nonlinear system and control nonlinear system based on neural network. The goal of this research is to evaluate a nonlinear adaptive neural network reference controller, in which a neural network model of a plant is used to identify the position system of marine helm and a neural network controller is used to control the output (actual position of marine helm) to achieve its desired value.

2. POSITION CONTROL SYSTEM OF MARINE HELM

Diagram of Position Control System

Figure 1 illustrates the block diagram of position control system of marine helm.

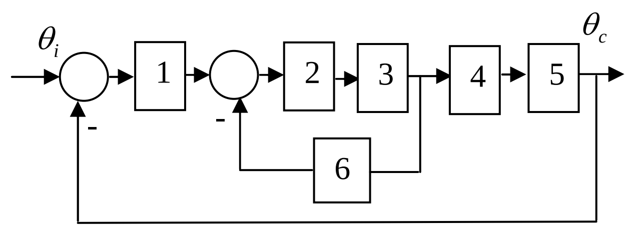

Figure 1 Block diagram of the position control system of marine helm

In the figure 1:
1-Preamplifier
2-Power amplifier with current feedback
3-DC motor
4-Gear train
5-Load
6-Tachometer
$\theta_i(t)$ -Desired position
$\theta_c(t)$ -Actual position

The objective of the control system is to have the output of the system $\theta_c(t)$ followed the input $\theta_i(t)$. In this control process, a number of control performance such as overshoot, settling time, steady error - just to name a few - have to be evaluated and controlled. Therefore, It is rather important to determine correct control approach to make the controlled variable reach its set point.

In the original control system which is shown in figure 1, the current feedback can compensate for the deviation caused by load current of motor and the position feedback can compensate for the deviation caused by disturbance or upset such change of parameter of system, ambient conditions and etc.

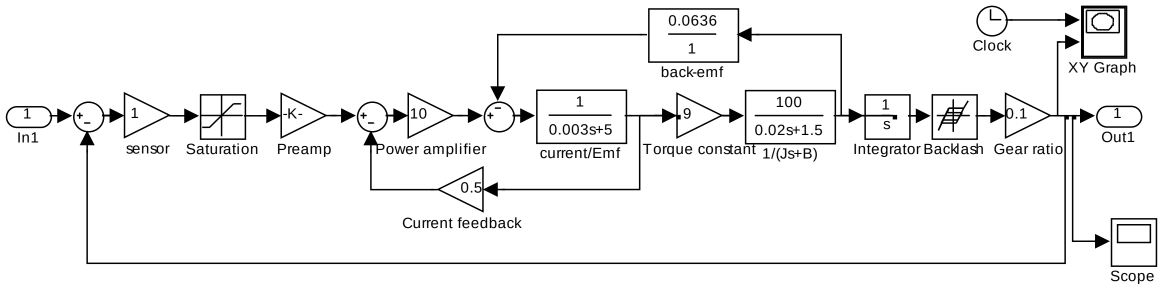

Figure 2 Transfer function block diagram of the position control system

The transfer function block diagram of the system is shown in figure 2.

Applying K=160, a comparison of two position outputs, of which with and without saturation of the amplifier and gear backlash in the position control system of marine helm, is shown in figure 3.

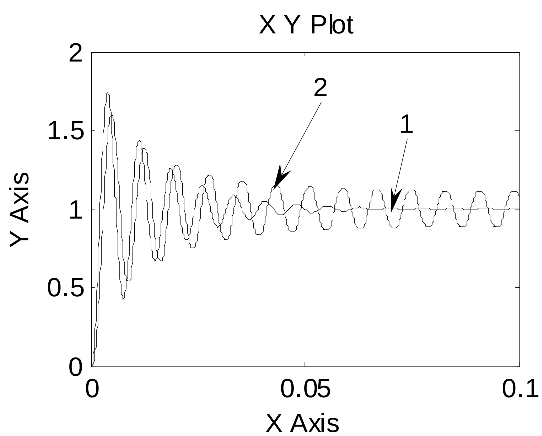

Figure 3 Output response of system without nonlinearity (curve 1) and with nonlinearity (curve 2)

In figure 3, curve 1 shows the output response assuming the system is linear while curve 2 shows the position response assuming the system has nonlinearities of saturation and backlash. The simulating result demonstrates that the output of the system $\theta_c(t)$ can not follow the command input $\theta_i(t)$ accurately when nonlinearity is considered. It is obvious that the output is trembling.

3. NEURAL NETWORK CONTROL SYSTEM

Control architecture

The objective of neural network controller is to identify the nonlinear system and control the output of the system $\theta_c(t)$ to trace the desired input value $\theta_i(t)$ accurately. At the same time, the control system must have satisfactory dynamic performance. In this paper, two neural networks are included. One is a plant model neural network and another controller network. They both are displayed in the Figure 4.

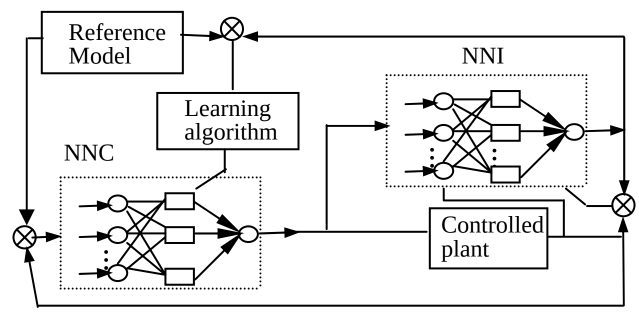

Figure 4 Control model with neural network

Each network has three layers, i.e. input-lay, hidden-layer and output-layer. The controlled plant is identified by plant model neural network first, and then the neural network controller is trained so that the plant output follows the reference model output.

System Identification

we select two delayed plant outputs and two delayed plant inputs as the inputs of the neural network plant model. Size of hidden layer is selected to ten. The sample data created by a random signal are used to train the plant-model neural network that can be represented the forward dynamics of the marine helm position system. The prediction error between the plant output and the neural network output is used as the neural network training signal. The neural network plant model uses previous inputs and previous plant outputs to predict the future values of the plant output.

We use Levenberg-Marquardt algorithm[6] as training function. When the performance function has the form of a sum of squares, the Hessian[7] matrix can be approximated as

$$H = J^T J \tag{1}$$

and the gradient can be computed as

$$g = J^T e \tag{2}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique[8]. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (3)$$

When the scalar μ is zero, this is just Newton's method[9], using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function.

In this way, the performance function will always be reduced at each iteration of the algorithm. For nonlinear position control system of marine helm, the training result, which demonstrates that the model neural network can identify the plant successfully, is shown in figure 5.

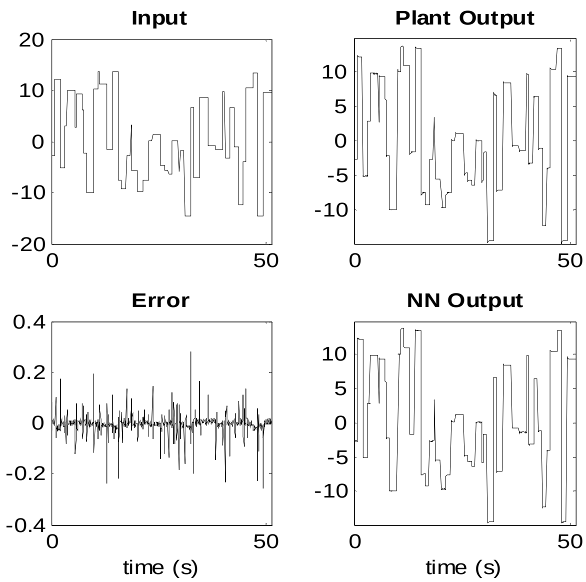

Figure 5 Testing result for Neural network

During the training we observed four different attractor states depending on the initial settings, three of which produced equally good performance (MSE < 0.5 on test set). A typical curve of convergence to the final value is presented in Figure 6. Obviously convergence is not uniform i.e. the weight space has a complex structure.

Reference model

For this position control system, since the electrical time constant is much smaller than the mechanical time constant, we can perform a crude approximation by neglecting the armature inductance. Therefore this third-order system can be regarded as a second-order system. We use a well-defined second-order system which has good performance as a reference model. This reference system must at minimum satisfy the three basic criteria of stability, accuracy, and a satisfactory transient response (eg. Overshoot, settling time).

Neural network controller

we design the neural network controller which has five inputs in input-layer, thirteen neurons in hidden-layer and one output in output-layer. The inputs to the controller consist of two delayed reference input, two delayed plant outputs, and one delayed controller output. Back-propagation created by generalizing the Widrow-Hoff[10] learning rule to multiple-layer networks and nonlinear differentiable transfer functions is the algorithm of the network.

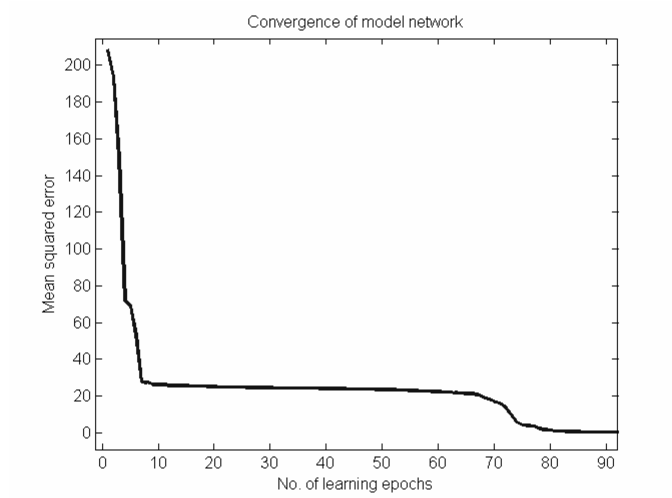

Figure 6: Typical learning curve for model network. Mean squared error is used as performance measure. A set of 20000 training patterns are presented every training epoch.

We can estimate the mean square error by using the squared error at each iteration. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

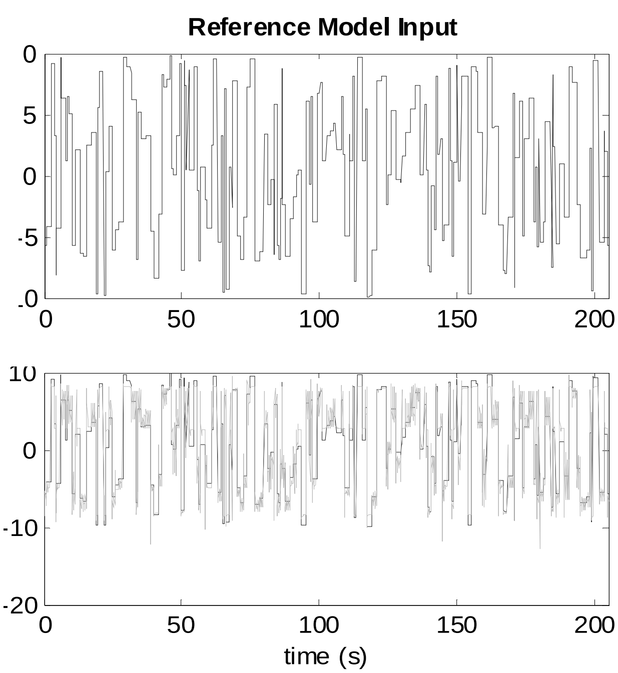

Figure 7 Comparison of reference model output (grey) and neural network output (black)

After training the neural network controller, we get the comparison of reference model output and neural network output as following figure 7.

Results

Let the command input be a unit-step function. We investigate three responses to three different control approaches. The simulation results are shown in Figure 8.

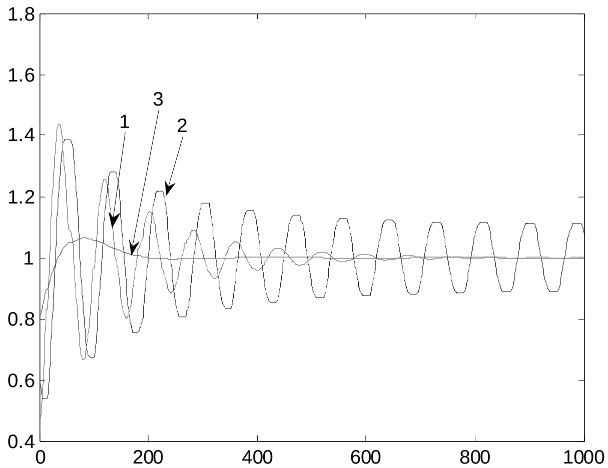

Figure 8 Simulation results of output response

The output response of position control system without saturation of the amplifier and gear backlash by using traditional PID controller (curve1); The output response of attitude control system with saturation of the amplifier and gear backlash by using traditional PID controller (curve 2); The output response of attitude control system with saturation of the amplifier and gear backlash by using reference neural network controller (curve 3).

From the simulation of output response, we get the following results:

1) When the system is simplified to a linear system that saturation of the amplifier gain and motor torque, gear backlash, and shaft compliances have all been neglected, we can improve the system performance by modifying the parameter of controller, using lag-phase compensation, ahead-phase compensation and lag-ahead-phase compensation.
2) When the nonlinearity of system is included, the output will may be oscillation that make output not be able to follow the reference object. PID controller is not sufficient to improve control performance of position system..
3) when the neural network controller, which we developed here, is adopted, the output response of the system with nonlinearity can trace the reference model better than traditional controllers. The overshoot decreases from 40% to 6%, while the response approaches to steady state rather quickly.

When we use a uniform random number signal, whose minimum is set to -1, maximum 1 and sample time 0.1, as a command input of the neural network controller, the output response simulation shows that controlled variable can also follow the command position accurately with good dynamic performance. The figure 9 illustrates the simulating result.

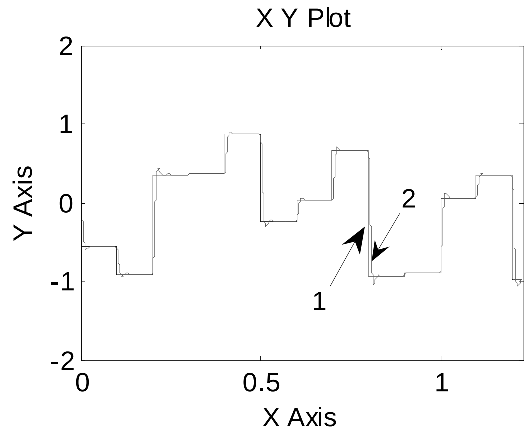

Figure 9 Response to uniform random number signal
Curve 1: Controlled position variable
Curve 2: Desired position output

4. DISCUSS

A method suitable for a position control of nonlinear marine helm has been proposed. The method is based on the application of a neural network reference control approach that incorporates the nonlinear saturation and backlash position control. Nonlinear properties are acquired during a learning phase Though just preliminary results are given in this paper the potential of neural networks to capture nonlinearity exhibited in position control system could be clearly demonstrated. A network was trained to model a plant with its nonlinearity. This trainings process has to be explored further to simplify the employed network structure and to guarantee convergence to an acceptable performance measure. Successively we utilized this trained neural network within a reference controller approach to control helm position to follow a desired target sequence accurately.

5. CONCLUSION

In practice, most system is nonlinear for large variations about the operating point, and linearization is based on the assumption that these variations are sufficiently small. But this cannot be satisfied, for example, for systems that include relay, saturation, dead-band, backlash, hysteresis and friction etc. the analysis and design techniques discussed in classical control theory are no longer valid, since the principle of superposition does not apply to nonlinear system. Worse, there is no general equivalent technique to replace them. Instead, a number of techniques exist, each of limited purpose and limited applicability. The describing function technique, for example, is a response method, and its main use is in stability analysis. it is difficult to analyse, identify, design and control the system with nonlinearities. For those more complex cases, it will be more difficulty to identification and control the system using traditional methods.

In this paper the applicability of neural network reference control to a position problem could be demonstrated. In the context of the marine helm this approach may prove to be valuable as it naturally extends to multidimensional problems. Results show that this approach can make the system output follow the command position accurately as well as successfully identify the nonlinear position system of marine helm .

In addition to position, some other parameters, such as speed, current and power etc., are important for optimizing system.

This study demonstrates that neural network reference control may prove valuable as a tool in position control system.

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