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RBF-Elman Neural Network Control on Electro-Hydraulic Load Simulator

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Abstract. Due to load simulation system existing strong disturbance, parameters time-variation and nonlinear, there was low control precision, poor adaptive abilityand robustnessin traditional control algorithm. In order to improve load simulation performance,The RBF-Elman neural network-based adaptive control method is presented.In this way, the load simulatorsystem isidentified by the RBF-Elmanneural networkidentifier, which provides model information (Jacobian matrix) to the PID controller and synchronous compensator in orderto make it adaptive. Back-propagation algorithms are used to train neural network. The PID controller which is designed by requirement for steady can overcome the shortcoming of the neural network controller. Finally, the simulations confirm that this control scheme results in a quick response, robustness, and excellent ability against disturbance.

Introduction

As a key equipment of hardware-in-loop loading simulation, The main function of the load simulator is reproduced rudder-suffered aerodynamic loads during the aircraft flight in the laboratory, in order to verify the control parameters of the aircraft control system, test load ability of rudder system, shorten aircraft development cycle, save development costs, improve reliability and success rate [1,2]. Load simulator has three forms: hydraulic, electric and pneumatic[3]. Due to hydraulic systems high power/mass ratio, fast response and high stiffness, electro-hydraulic load simulators arewidely used.Hydraulic systems are complex and pose nonlinearities, whichmakes the modeling and design of feedback controllers challenging. The nonlinearities mainly remain in servo valve flow-pressure characteristics,orifice area openings,variations of fluid volume under compression and in part, mechanical friction, damping coefficient, viscosity and elasticity of oil[1,4,5]. In this condition, conventional PID controllers do not yield reasonableperformance over a wide range of operating conditions and meet the requirements of control precision,simultaneouslyability against disturbance is poor. Therefore, adaptive, self-learning and high-precision is urgent needs of a new load simulator.

When Radial basis function (RBF) neural network simulates nonlinear continuous function,it hasfast learning speed, small calculation and no local extrema, whichcan be appliedtoreal-timecontrol [6]. However, lack of the feedbackinformation, feedforward network structure can’t identifydynamic systems effectively,which is difficult to meet the high precision control of dynamic systems. So RBFis integratedwith dynamic recurrent neural network,which can improve approximation and identification of dynamic systems and take advantage of RBF rapid calculation andno local extrema. Therefore, the RBF-Elman neural network (RENN) application in real-time and high precision load simulator control system is possible.So, on the one hand, neural network integrated with PID controller (NNPID), based onconventional PID controller, use neural network adaptive ability to fine-tune the system control parameters and constitute self-tuning, stabilizing controller [7,9]. On the other hand, neural networkcompensator (NNC)is builtbased on the principles of velocity synchronizing control [1],fine-tuning synchronous control parameters for disturbance-reduced.

RBF-Elman Neural Network Model

Elman is an important type of recurrent neural networks, because of the addition of the layer or layers feedback connections,therefore it has been widely used in control engineering fields. Based on Elman neural network, three RENNstructure[11] is shown in Fig. 1. Compared with feedforward neural network, besides the input layer, hidden layer and output layer, RENNhas a special structural unit called context unit,which is used to receive and memory hidden layer historical information,so it is regarded as a delay operator.

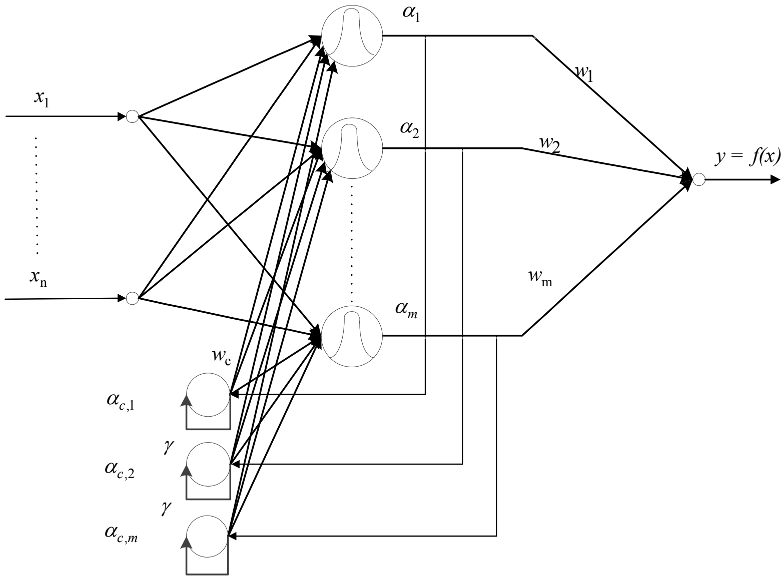


Fig.1RENN structure diagram

The first layer is the input layer, the layer is connected directly to input value whichis transferred to the next layer.

The second layer is hidden layer, whose role is nonlinear mapping using Gaussian function, where, the input-output relationship is:

$$s(j)=\sum_{l=1}^{m}\omega_{jl}^{1}\alpha_{c,l}(k)+\sum_{i=1}^{n}x \tag{1}$$

$$\alpha_{c,l}(k)=\gamma\bullet\alpha_{c,l}(k-1)+\alpha_l(k-1) \tag{2}$$

$$\alpha_j(k)=f[s(j)]=\exp[-(\frac{s(j)-c_l}{\sigma_l})^2] \tag{3}$$

Where: $i=1,2,...,n$, $j=l=1,2,...,m$, ω_{jl}^{1} are weights context unit to hidden layer, α_j are hidden layer output, $\alpha_{c,j}(k)$ are context unit output, c_l and σ_l is the center and width of the Gaussian function. γ is context unitfeedback gain, s represents the total inputto hidden layer unit, k means the number of iterations.

The third layer is the output layer, the weighted sum of hidden layer output:

$$y(k)=\sum_{l=1}^{m}w_l^2\alpha_l(k) \tag{4}$$

Where: y is the output of neural network output layer, w_l^2 are weights hidden layer to output layer.

RENN-basedControlSchemeonElectro-HydraulicLoad Simulator

In this section, asshown in Fig. 2,the RENN is derived to modelthe load simulatorsystem, and then a neural networkPID controller and compensator are designed to controlit. The control objective is to tune the parameters in the RENNidentifier so that itsoutput Mm(k) can model the system nonlinear behavior M(k) in realtime,at thesame time,to tunethe parameters in the NNPID controller and NNC so that the output M(k) ofthe nonlinear system tracks the desired trajectories Mr(k).Therefore, the RENN identifier can provide updated modelinformation (Jacobian matrix) to the NNPID controller and NNCevery timestep [13].

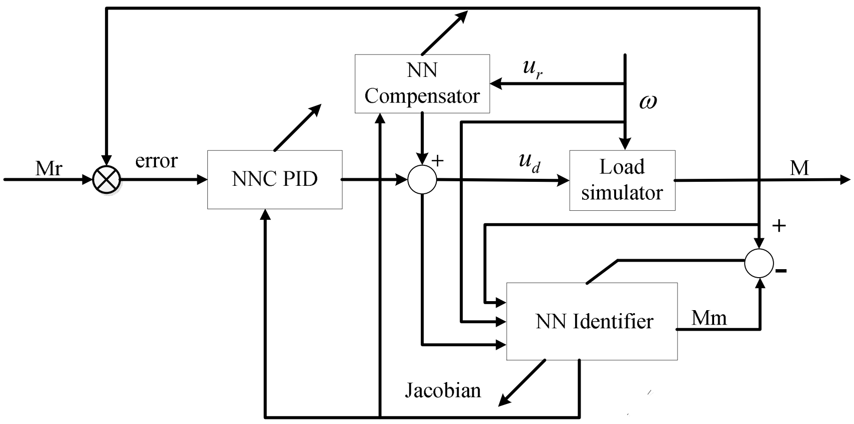


Fig. 2Based on RENNadaptiveneural networkcontrol system block diagram

Neural network identifier. When neural network identifier (NNI)is used to approach power actuator transfer function, model identification accuracy directly determines the neural network control precision. Load Simulator servo valve control signal,torque Sampling and rudder angular velocity areused as NNIinputs.

$$X=[x_1,x_2,x_3]^{\mathrm{T}}=[u,M,\omega]^{\mathrm{T}} \tag{5}$$

In the neural network training strategy, the weights are updated by BP algorithm.The performance targetof identification is givenas

$$E_m=\frac{1}{2}[M(k)-M_m(k)]^2=\frac{1}{2}e^2(k) \tag{6}$$

Where: $M(k)$, $M_m(k)$ and $e(k)$ arethe load simulator output, the RENN output and the identification error,respectively. The optimization target ischaracterized to minimize the error function Eq. (6) with respectto the adjustable parameter of the network.

By gradient descent method, the neural NNIupdate rule is calculated as

$$\begin{aligned} &w_l^2(k+1)=w_l^2(k)-\eta_{w^2}\frac{\partial E_m}{\partial w_l^2}\Big|_k \qquad \omega_{jl}^1(k+1)=\omega_{jl}^1(k)-\eta_{\omega^1}\frac{\partial E_m}{\partial \omega_{jl}^1}\Big|_k \\ &c_j(k+1)=c_j(k)-\eta_c\frac{\partial E_m}{\partial c_j}\Big|_k \qquad \sigma_j(k+1)=\sigma_j(k)-\eta_\sigma\frac{\partial E_m}{\partial \sigma_j}\Big|_k \end{aligned} \tag{7}$$

Connection weights w_l^2 hidden layer to output layeris calculated as

$$\frac{\partial E_m}{\partial w_l^2}\Big|_k=\frac{\partial E_m}{\partial M_m(k)}\bullet\frac{\partial M_m(k)}{\partial w_l^2}=-(M_m(k)-M(k))\bullet\alpha_l(k) \tag{8}$$

Connection weights ω_{jl}^1 context unit to hidden layeris calculated as

$$\frac{\partial E_m}{\partial \omega_{jl}^1}\Big|_k=\frac{\partial E_m}{\partial M_m(k)}\bullet\frac{\partial M_m(k)}{\partial \alpha_l(k)}\bullet\frac{\partial \alpha_l(k)}{\partial \omega_{jl}^1}=-(M_m(k)-M(k))\bullet\omega_l^2(k)\bullet\frac{\partial \alpha_l(k)}{\partial \omega_{jl}^1} \tag{9}$$

Where:

$$\frac{\partial \alpha_l(k)}{\partial \omega_{jl}^1}=f^{'}(\bullet)[\alpha_{c,l}(k)+\sum_{j=1}^{m}\omega_{jl}^1\frac{\partial \alpha_{c,l}(k)}{\partial \omega_{jl}^1})] \tag{10}$$

Not consider $\alpha_{c,j}(k)$ dependenceon weight ω_{jl}^1, itis simplified as

$$\begin{aligned} \frac{\partial \alpha_l(k)}{\partial \omega_{jl}^1}&=f^{'}(\bullet)\alpha_{c,l}(k)=f^{'}(\bullet)\alpha_l(k-1)+\gamma\bullet f^{'}(\bullet)\alpha_{c,l}(k-1) \\ &=f^{'}(\bullet)\alpha_l(k-1)+\gamma\bullet\frac{\partial \alpha_l(k-1)}{\partial \omega_{jl}^1} \end{aligned} \tag{11}$$

Center parameter c_l is calculatedas

$$\left.\frac{\partial E_m}{\partial c_l}\right|_k = \frac{\partial E_m}{\partial M_m(k)} \bullet \frac{\partial M_m(k)}{\partial \alpha_l(k)} \bullet \frac{\partial \alpha_l(k)}{\partial c_l} = -(M_m(k) - M(k)) \bullet \omega_l^2(k) \bullet \frac{2\alpha_l(k)[s(l) - \bar{c}_l(k)]}{\sigma_l(k)^2} \quad (12)$$

Similarly, width parameter σ_l is calculated as

$$\left.\frac{\partial E_m}{\partial \sigma_l}\right|_k = \frac{\partial E_m}{\partial M_m(k)} \bullet \frac{\partial M_m(k)}{\partial \alpha_l(k)} \bullet \frac{\partial \alpha_l(k)}{\partial \sigma_l} = -(M_m(k) - M(k)) \bullet \omega_l^2(k) \bullet \frac{2\alpha_l(k)[s(l) - c_l(k)]^2}{\sigma_l(k)^3} \quad (13)$$

From above derivation, for the adjustment of weights ω_{jl}^1 structural unit to hidden layer, Eq. (11)constitutes a dynamic recursive relation of gradient $\frac{\partial \alpha_l(k)}{\partial \omega_{jl}^1}$, so RENNcan identify high order systems.

$\frac{\partial M}{\partial u}$ isJacobian information of the controlled object. $\frac{\partial M_m}{\partial u}$ is obtained through RENN online identification on load simulation. When NNIapproach the controlled objectaccurately, $\frac{\partial M_m}{\partial u}$ can replace $\frac{\partial M}{\partial u}$ as Jacobianmatrix.

$$\frac{\partial M}{\partial u} \approx \frac{\partial M_m}{\partial u} = \sum_{l=1}^{m} \frac{\partial y(k)}{\partial \alpha_l(k)} \bullet \frac{\partial \alpha_l(k)}{\partial z_j} \bullet \frac{\partial z_j}{\partial \Delta u} = \sum_{j=1}^{m} w_j^2 \bullet f' \bullet \frac{2[c_j(k) - u]}{[\sigma_j(k)]^2} \quad (14)$$

Neural network controller.RENN can automatically memory part of the historical information and is more suitable for nonlinear dynamic system identification for the reason of internal dynamic feedback link.Therefore neural network controller can accurately track the electro-hydraulic load simulator model changes, so proposed control scheme can update NNPID control parameters in real time using NNI to ensure the good characteristics of the system.

Conventional PID control principle is givenas the following formula

$$error(k) = M_r(k) - M(k) \quad (15)$$

$$xc(1) = error(k) - error(k-1), \quad xc(2) = error(k)$$
$$xc(3) = error(k) - 2error(k-1) + error(k-2) \quad (16)$$

$$u_1(k) = u_1(k-1) + \Delta u_1(k), \quad \Delta u_1(k) = k_p xc(1) + k_i xc(2) + k_d xc(3) \quad (17)$$

Error function is given as

$$E_l(k) = \frac{1}{2} error(k)^2 \quad (18)$$

Three control parameters can be updated respectivelythrough thegradientdescent method

$$\Delta k_p = -\eta \frac{\partial E_l}{\partial k_p} = -\eta \frac{\partial E_l}{\partial M} \bullet \frac{\partial M}{\partial u} \bullet \frac{\partial u}{\partial k_p} = \eta error(k) \frac{\partial M}{\partial u} xc(1) \quad (19)$$

$$\Delta k_i = -\eta \frac{\partial E_l}{\partial k_i} = -\eta \frac{\partial E_l}{\partial M} \bullet \frac{\partial M}{\partial u} \bullet \frac{\partial u}{\partial k_i} = \eta error(k) \frac{\partial M}{\partial u} xc(2) \quad (20)$$

$$\Delta k_d = -\eta \frac{\partial E_l}{\partial k_d} = -\eta \frac{\partial E_l}{\partial M} \bullet \frac{\partial M}{\partial u} \bullet \frac{\partial u}{\partial k_d} = \eta error(k) \frac{\partial M}{\partial u} xc(3) \quad (21)$$

The scheme is based on the traditional PID control theory, which can follow the classical stability theory to determine the range of control parameters to solvethe ubiquitousunstable issues in neural network controller.In order to ensure stable operation of the system, the control parameters varies in the following range

$$k_{p\min} \le k_p \le k_{p\max}, \quad k_{i\min} \le k_i \le k_{i\max}, \quad k_{d\min} \le k_d \le k_{d\max}$$

Neural networkcompensator.NNC is based on velocity synchronizing control to compensate disturbance, whose input is rudder servo valve control signal.

Load simulator control signals u include two parts: NNPID controller value u_1 and NNC u_2.

$$u = u_1 + u_2 \qquad (22)$$

The structure of NNCis single-layer network, the output is

$$u_2(k) = u_2(k-1) + \Delta u_2(k), \quad \Delta u_2(k) = k_r(u_2(k) - u_2(k-1)) \qquad (23)$$

Similarly, NNC parameter isupdated as

$$\Delta k_r = -\eta_b \frac{\partial E_l}{\partial k_r} = -\eta_b \frac{\partial E_l}{\partial M} \bullet \frac{\partial M}{\partial u} \bullet \frac{\partial u}{\partial k_r} = \eta_b error(k) \frac{\partial M}{\partial u}(u_2(k) - u_2(k-1)) \qquad (24)$$

Similarly, in order to ensure stability, the compensation parameters vary in the following range

$$0 \le k_r \le k_{r\max}$$

Simulation Analysis

Load simulator and rudder system model is created using AMEsim dynamic simulation integrated environment, neural network control system is created using Matlab-Simulink environment. Through co-simulation between Matlab and AMEsim, the ability against disturbanceand dynamic tracking characteristics of the proposed method is verified.

Extraneous Torque Eliminating. In simulation, rudder motion: $\theta(t) = 5\sin(4\pi t)$ .Load simulator instruction is 0.

Fig. 3 shows a comparison of extraneous torque eliminating between conventional PID controller and neural network controller.It is seen from Fig.3, the extraneous torque produced by proposed RENN-based intelligent control method is too much smaller than that produced byconventional PID control method.NNPID controller can achieve a better elimination effect. Thereason is that the neural network controller can adjust parameters in real time according totracking errorchanges, reduce extraneous torque, enable the system to track load spectrum accurately.

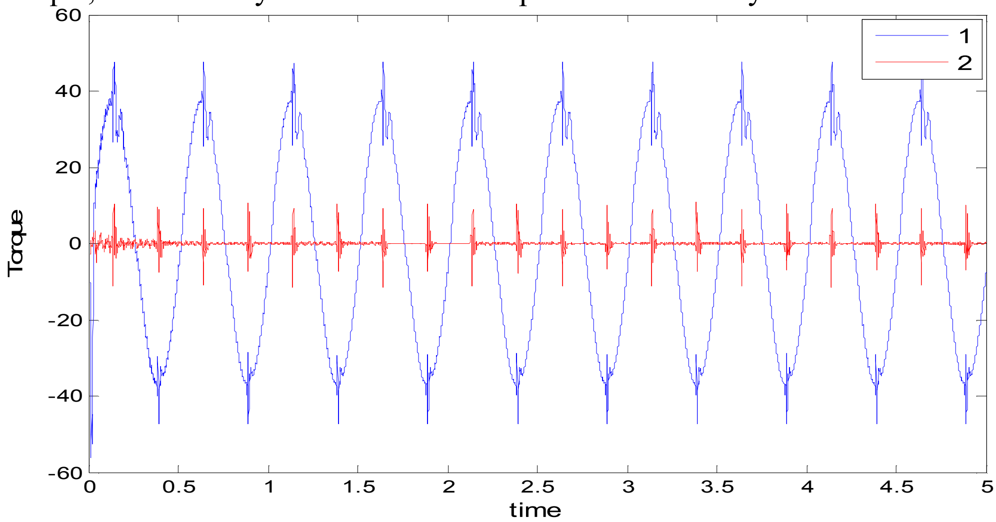
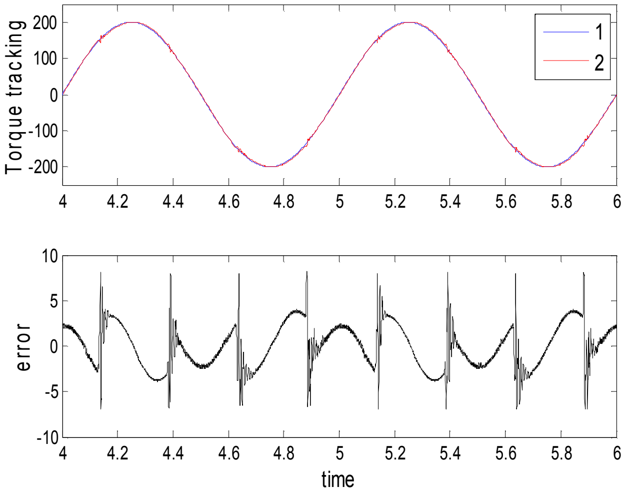


Fig. 3a comparison of extraneous torque eliminating
1. Conventional PID controller method 2.RENN-based intelligent control method

In control process, extraneous torque mutation of load simulation occurred in rudder commutation process.

Dynamic Load Tracking. Rudder motion: $\theta(t) = 5\sin(4\pi t)$ .Load simulator istrackingtestedunder different frequency sinewave.It is seen from Fig. 4 and Fig.5,which show sinusoidal load spectrum tracking.Neural network control scheme not eliminate extraneous torquesimply, but use extraneous torque to compensate system tracking lag, which reflect neural network adaptive and self-learning ability. In addition, neural network excellent nonlinear mapping ability results in a quick response, mini phase lags and high control precision.



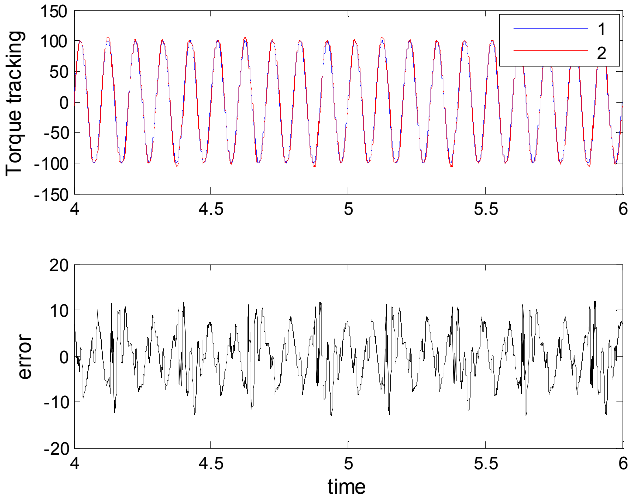


Fig.4 1Hz sin wave trackingerrorFig.5 10Hz sin wave tracking error

1.Given load command

2. System load output

Judging from the overall effect, the proposed control method has good tracking speed, robustness and control precision. This is because neural network nonlinear mapping and adaptive ability can solve electro-hydraulic load simulator system nonlinearity, uncertainty and time-variation.Therefore it can get good control effect.

Conclusions

The RBF-Elman neural network-based intelligent PID controller mainly use RBF-Elman high precision function approximation ability to trackthe object model change in realtime, on the basis, adjustingcontrol parameters of neural network-based PID controller and compensator,finally, theproposed control scheme can achieve a high control precision. Since neural network PID controller is based on PID control theory, parameters variation rangesare limited to stability theory,which can ensures the stability of system and improves the convergence speed. Furthermore, neural network compensator is based on velocity synchronizing control theory for extraneous force compensation, using neural network adaptivity to achieve a good eliminating effect.

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