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Research of Dynamic Parameter Identification of LuGre Model Based on Weights Boundary Neural Network

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Abstract. The identification problem on the dynamic parameters in LuGre model is studied. The identification method proposed uses a neural network which considers weights boundary. The network structures and weight adjustment algorithm are given out. In order to find a set of parameters to make it approach the actual one, this algorithm uses neural network identification within the bounds of the identified parameters. Compared with the non-linear least squares (NLS) parameter identification, the relative errors of parameters which are identified by neural network based on weights boundary (WBNN) are smaller, and the precision is higher. Numerical simulation is provided to show the efficiency of the proposed method

Keywords: neural networks,weight boundary,LuGre model,dynamic parameters identification

1. Introduction

The concept of identification and control on LuGre friction model was investigated quite intensively in recent years, because of non-linearity of its model, immeasurability of its internal state variables and coupling effect with static and dynamic parameters[1][2]. Wang et al. [3] obtained more precise friction model using the method of combining offline identification with online observation. Madi, M.S et al. [4] proposed a bounded-error estimation approach based on interval analysis and set inversion. Two different friction model parameter identification methods were presented by Wu et al. [5] from the time and frequency domain. Reference [6] - [9] used the genetic algorithm, adaptive ant colony algorithm and particle swarm algorithm to identify the friction parameters of the servo system.

Previous researches mentioned above have failed to consider that the actual system parameter values may only be a local optimum. It made the identification results differ greatly from the real parameter values, and took a longer time in identification process, for all that methods searched the eligible optimal value from the entire number axis. In order to overcome these limitations, this paper put forward a new neural network identification method which considers weights boundary. The purpose of it is to find a set of parameters to make it approach the actual one within the bounds of the identified parameters.

2. Neural Network Parameter Identification Based on Weights Boundary

The BP network model is not very clear correspondence with the structural model of the recognized system, therefore the network structure on BP is arbitrary. If you use a system structure of the neural network agreeing with the actual one for system parameter identification, it will be easier to get convergence results. To do this a neural network model which links with the actual system structure should be adopted firstly, then the value of upper and lower bounds of each parameter be determined, and the initial value be selected between this boundary according to the past experience and actual practical engineering or theoretical calculations. This will ensure that the parameters are in the upper and lower bounds in the identification process, so that the identification results will consistent with the real system.

2.1. Network Structure

To make the constructed neural network model to be consistency with the structure of the real system , the system mathematical model is need to be understood, and the topology structure of neural network is constructed. We can use a number of simple neurons and weight of its argument, through a certain connection to represent a complex system. This network not only has the clear physical meaning, the network structure (number of layers and the number of neurons) is also consistent with the structure of the system, and more importantly, the weights of the network also include the system parameters.

The general neural network system parameters identification model are shown in Fig.1.The neural network output is denoted in Fig.1 as *Y*, the network input is *X*, *f(k)* is activation function, and *φ(X)* is an arbitrary function determined by the actual system.

2.2. Weight Adjustment Algorithm

System model is given by the followed equation:

$$y(k) = \sum_{i=1}^{m} b_i u(k-i) - \sum_{i=1}^{n} a_i y(k-i) \tag{1}$$

We seek to identify the system parameters $\theta=[a_1,a_2,\ldots a_n,b_1,b_2, \ldots b_m]^T$ by using input and output time series $\{u(k), y(k)\}$ and optimization criterion function. Therefore we can take neural network as a system parameter identifier. Through the network training, the weights of the network can become the estimated values of system parameter, it can be written as:

$$\hat{\theta} = W = [w_1, w_2, \cdots, w_N] = [\hat{a}_1, \hat{a}_2, \cdots \hat{a}_n, \hat{b}_1, \hat{b}_2, \cdots \hat{b}_m]^T$$

where N=n+m. The output of neural network parameter identifier is given as

$$\hat{y}(k) = h_{sp}^T(k) \cdot W(k) \tag{2}$$

where $h_{sp}^T(k)=[h_1(k), h_2(k), \ldots h_N(k)]^T=[-y(k-1), \ldots -y(k-n), -u(k-1), \ldots -u(k-m)]^T$.

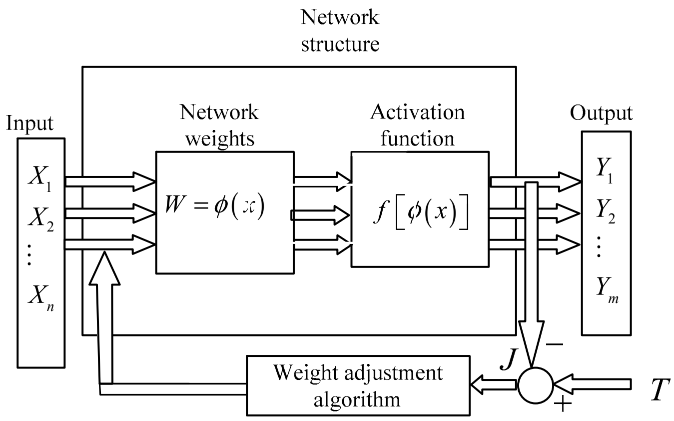

Fig. 1: The neural network parameters identification model with weights boundary

To determine the parameters of the estimated value *W(k)* in the sampling point, it must be made the value of criterion function as following (3) is the minimum.

$$\mathrm{E}(W,k) = \frac{1}{2}(y(k) - \hat{y}(k))^2 \tag{3}$$

From the initial weight W(0) start, the neural network training use rule δ, that is the weights change along the fastest fall direction. Weight variation is obtained by (2) and (3):

$$\Delta W(k) = -\eta(k)\frac{\partial E(W,k)}{\partial W} = \eta(k)[y(k) - \hat{y}(k)]h_{sp}(k) \tag{4}$$

Where $\eta(k)=\alpha/\|h_{sp}(k)\|^2$, α is a constant, $0<\alpha<2$.

Weights recursive formula can be combined with (2) and (4):

$$W(k+1) = W(k) + \eta(k)[y(k) - \hat{y}(k)]h_{sp}(k)$$
$$= W(k) + \eta(k)[y(k) - h_{sp}^T(k)W(k)]h_{sp}(k) \quad (5)$$

When weight W_i adjusted by (5) is not the value within the range of maximum W_{imax} and minimum W_{imin}, it will be set to the boundary value.

2.3. Parameter Identification Procedure

Step1: Take initial weights W(0) between its upper and lower bounds;

Step2: Calculate the output of neural network $\hat{y}(k)$ by constructing the neural network model;

Step3: Combined with neural network output, calculate error $e(k) = y(k) - \hat{y}(k)$;

Step4: Neural network weights will be adjusted to:

$$W(k+1)=W(k)+\Delta W(k);$$

Step5: Analysis whether the weight is within the allowable range. If it is, go to Step (6); if not then

while $W_i > W_{imax}$, $W_i = W_{imax}$;

while $W_i < W_{imin}$, $W_i = W_{imin}$;

Step6: Calculate, determine whether it is in the range of allowable error. If it is OK, then stop identification. If not, go to Step3.

3. Servo stable Platform with LuGre Friction Model

Structure of rotary steering drilling stable platform with LuGre friction model [10] [11] is shown in Fig.2.

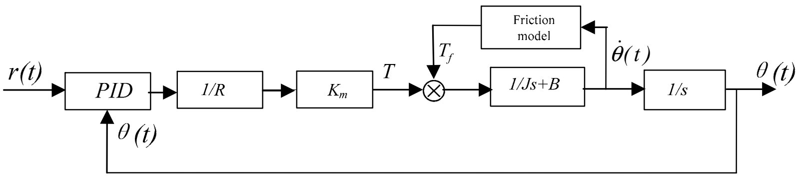

Fig.2: The block diagram of rotary steering drilling stable platform with Lugre friction model

Where *r(t)* is the setting tool face angle, θ is the actual tool face angle of stable platform, $\dot{\theta}(t)$ is the platform speed, *R* represents the armature resistance, K_m is the motor torque coefficient, *J* is moment inertia of stable platform, *T* represents control torque, T_f represents the friction torque.

Steerable drilling stable platform servo system can be expressed with the following differential equation:

$$J\ddot{\theta} = T - T_f \quad (6)$$

The friction model applied with LuGre model, its expression is as follows:

$$T_f = \sigma_0 z + \sigma_1 \frac{dz}{dt} + B\dot{\theta} \quad (7)$$

$$\frac{dz}{dt} = \dot{\theta} - \frac{|\dot{\theta}|}{g(\dot{\theta})} z \quad (8)$$

$$\sigma_0 g(\dot{\theta}) = T_c + (T_s - T_c)e^{-(\dot{\theta}/\dot{\theta}_s)^2} \quad (9)$$

Where T_c is the Coulomb friction torque; T_s is the maximum static friction torque; *B* is the viscous friction coefficient; $\dot{\theta}_s$ represents the Stribeck angular velocity; σ_0 is the stiffness coefficient of microscopic deformation z; σ_1 represents the viscous damping coefficient.

4. LuGre Model Dynamic Parameter Identification

For the static parameters of LuGre model, such as T_c, T_s, *B* and $\dot{\theta}_s$, the Stribeck curve recognition could be utilized [8]. However, for dynamic parameters identification, the neural network with weights boundary (called as WBNN) method proposed in the previous sections should be adopted.

When the system is affected by control moment but still in a quiescent state, it means that the system has no apparent movement, we can suppose:

$$z = \theta, \frac{d\theta}{dt} \approx \dot{\theta} \tag{10}$$

Therefore (7) can be approximately written as:

$$T_f = \sigma_0 \theta + \sigma_1 \dot{\theta} + B\dot{\theta} \tag{11}$$

So the system model can be given by

$$J\ddot{\theta} + (\sigma_1 + B)\dot{\theta} + \sigma_0 \theta = T \tag{12}$$

Laplace transforming of (12) gives

$$\frac{\theta(s)}{T(s)} = \frac{1}{Js^2 + (\sigma_1 + B)s + \sigma_0} \tag{13}$$

Then after discreting , the following equation can be obtained:

$$T(k)=-2T(k-1)-T(k-2)+\sigma_0[\theta(k)+2\theta(k-1)+\theta(k-2)]+\sigma_1[\theta(k)-\theta(k-2)]$$
$$+J[\theta(k)-2\theta(k-1)+\theta(k-2)]+B[\theta(k)-\theta(k-2)] \tag{14}$$

Based on past experience and theoretical calculations, the range W_i can be obtained, in which maximum and minimum are W_{max}=[4,2,3,4,5,2] and W_{min}=[-5,-3,-4,-2,-3,-2] respectively.

Using neural network as the system parameters identifier according to the parameter bounds, a set of initial values which must be between the maximum and minimum value can be selected, such as W(0)=[-3,1,2,2,3,1].

The neural network model established by the above principles is shown in Fig.3. Neural network input composes by the system input *θ (k)* and *T(k)* output.

Parameter W_i is identified according to the WBNN algorithm described previously. After the neural network training, we have

W=[-2.0053,0.9974,0.5103,0.3818,1.0048,0.0073]

Thus the stiffness coefficient σ_0 and viscous damping coefficient σ_1 of the Lugre friction model are as shown in Fig. 4.

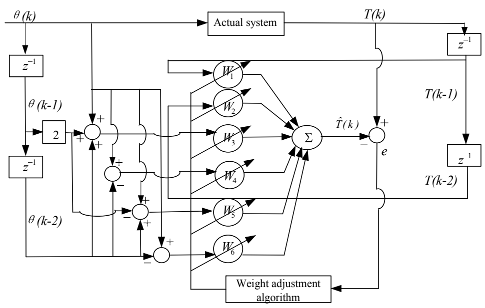

Fig.3 : The principle diagram of WBNN model

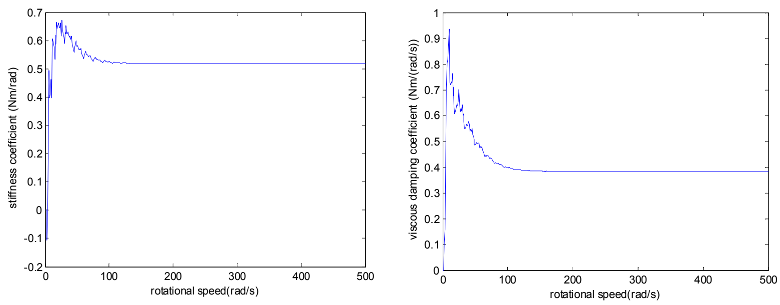

Fig.4 : (a) Stiffness coefficient σ_0 (b) Viscous damping coefficient σ_1

It shows that the relative error of NLS is much larger than WBNN in the process of dynamic parameter identification and the parameter identification accuracy of WBNN is much higher than NLS from the above Table 1 and Table 2. So the WBNN is more suitable for the dynamic parameter identification of Lugre friction model.

Table 1. WBNN dynamic parameter identification results

dynamic parameter	real value	identification results	relative error
σ_0	0.50	0.5103	0.21%
σ_1	0.40	0.3818	4.55%

Table 2. NLS dynamic parameter identification results

dynamic parameter	real value	identification results	relative error
σ_0	0.50	0.4766	4.68%
σ_1	0.40	0.2701	32.47%

5. Conclusion

The current paper presented a neural network identification method with weights boundary for the dynamic parameters identification for Lugre friction model. The parameter identification results using the WBNN compensation shows smaller relative error and higher accuracy than those using the NSL. The WBNN identification algorithm has proved to be a very effective and efficient in this dynamic parameter identification of Lugre friction model procedure.

6. Acknowledgment

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