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INTELLIGENT CONTROL FOR MODEL-FREE ROBOT JOINT WITH DYNAMIC FRICTION USING WAVELET NEURAL NETWORKS

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ABSTRACT

In this article, an intelligent compensation control algorithm for low-speed robot joint with dynamic friction was proposed based on self-recurrent wavelet neural networks (SRWNN). It is not necessary to predict the dynamic model parameters, and the high-precision compensation of nonlinear friction is realized by using few neurons and iterations through only position feedback. Lyapunov stability analysis results show the bounded convergence of tracking error and network weights. The servo experimental results from a certain type of robot joint show that the positioning accuracy can be greatly improved by introducing the proposed intelligent algorithm.

Keywords: *Model-Free, Friction Compensation, Self-Recurrent Wavelet Neural Networks (SRWNN), Compensation Control*

1. INTRODUCTION

Friction is the bottleneck for low-speed servo drive system [1] to improve the dynamic and static performance, and it can cause some malpractices such as phase-lag, repeatability deterioration, stick-slip motion, commutation error and waveform distortion, etc. Therefore, the study of friction compensation has been an important issue in the field of precision motion control.

Friction compensation control method can be divided into model compensation and model-free compensation. The current research results have shown that the friction is a complex nonlinear function which has zero gap and piecewise continuous characteristics. The friction model parameters are related with shaft structure, lubrication condition, temperature, load type and servo speed, etc. Since the time-varying characteristic of influencing factors, it is difficult to directly use fixed friction model to compensate. Genetic algorithm is a kind of approach for nonlinear identification [2]. Jiao proposed a genetic algorithm to identify the friction model parameters and to make the compensation term continuously approach the actual friction [3]. Zhou proposed an adaptive coulomb friction model based on the SVM (support vector machine) regression, and the inaccurate modeling problem caused by discontinuous friction torque at zero-speed was solved [4]. In [5], the online estimation and compensation for friction is realized through the fuzzy adaptive adjustment. A friction compensation method by using the friction state observer with time-varying gain is proposed in [6]. Model-free compensation method regards friction as a kind of nonlinear disturbance of the system，and uses the robust method to stabilize the output，thus it is not necessary to detect the friction parameters. The representative methods are as follows: high gain PID control (i.e., in [7]), friction estimation and compensation based on extended Kalman filter (i.e., in [8]), the robust control based on the disturbance observer (i.e., in [9]), etc. In recent years, the neural networks [10], such as BP, RBFN, Gauss, etc., has been successfully applied in the nonlinear domain for the capability of high precision approximation to the continuous functions. However, for the nonlinear functions with piecewise, discontinuous characteristics, the approximation ability is limited even if using more neurons and iterations. Rastko proposed a neural network structure with additional jump-neurons to approximate the piecewise continuous functions [11]. Kemal established a

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Sigmoid feed-forward neural network with only one speed-input node to compensate the friction [12]. An extension neural network with ogee jump activation function was designed to compensate friction in [13], but the neurons threshold of activation function must be set at the discontinuity point of approximated function. Seong used a regression fuzzy neural network to compensate the dynamic friction, and realized the high precision positioning of the position servo system [14]. The CMAC neural network is employed to realize the local approximation and feed-forward compensation control of nonlinear friction in [15]. Wavelet neural networks (WNN) is different from the above mentioned neural networks [16]. It is developed in the framework of multi-resolution analysis, and has the ability to extract the signal detail components. Hence, WNN can be used to approximate the discrete nonlinear functions. In this paper, an intelligent control algorithm for friction compensation based on self-recurrent wavelet neural network is proposed, and the experimental results are shown.

2. STRUCTURE OF SELF-RECURRENT WAVELET NEURAL NETWORK

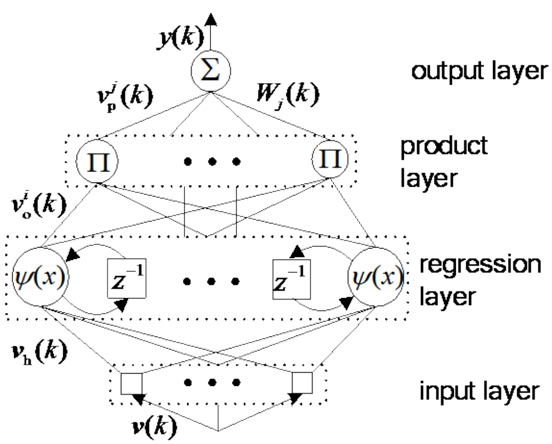

Figure 1 Self-Recurrent Wavelet Neural Network

Self-recurrent wavelet neural network is a dynamic feedback network, and it has the mapping function of the dynamic characteristics by storing internal state, thus the network has the time-varying characteristics. The compactly supported wavelet makes the self-recurrent wavelet neural network has superiority at approximation of the revulsion and discontinuous functions.

Design a self-regression wavelet neural network structure with four layers, namely, input layer, the regression layer, the product layer and output layer, as shown in Figure 1. The variable symbols are as follows:

k —Servo cycle number;

$\boldsymbol{v}(k)$ —Input vector of the input layer;

$\boldsymbol{v}_{\mathrm{h}}(k)$ —Input vector of the regression layer;

$v_{\mathrm{h}}^{i}(k)$ —The i-th variable of the regression layer input vector;

$\psi(x)$ —Activation function of the regression layer neurons;

$v_{\mathrm{o}}^{i}(k)$ —Output of the i-th neuron in the regression layer;

$v_{\mathrm{p}}^{j}(k)$ —Output of the j-th neuron in the product layer;

$W_j(k)$ —Ideal weights of the j-th neuron of the product layer and output layer;

$y(k)$ —The network output.

The network output is

$$y(k)=\sum_{j=1}^{N_j} W_j(k)\cdot v_{\mathrm{p}}^{j}(k) \tag{1}$$

where N_j is the number of product layer neurons.

The network product layer output is

$$v_{\mathrm{p}}^{j}(k)=\prod_{i=1}^{N_i} v_{\mathrm{o}}^{i}(k) \tag{2}$$

where N_i is the number of regression layer neurons.

The network regression layer output is

$$v_{\mathrm{o}}^{i}(k)=\psi\left(v_{\mathrm{h}}^{i}(k)\right) \tag{3}$$

where the activation function of the regression layer neurons is the Mexican-Hat wavelet function

$$\psi(x)=(1-x^2)\cdot\exp(-x^2/2) \tag{4}$$

The input vector of the regression layer is

$$\boldsymbol{v}_{\mathrm{h}}(k)=[\boldsymbol{v}(k) \quad v_{\mathrm{o}}^{i}(k-1)] \tag{5}$$

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The input vector $\boldsymbol{v}(k)$ of the input layer can be defined in accordance with the control object and the measured state variable.

3. INTELLIGENT CONTROL ALGORITHM BASED ON FRICTION COMPENSATION

3.1 SYSTEM MODEL

The dynamics equation of robot joint position servo system can be expressed as

$$M(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta} + K(\theta) + F(\dot{\theta}) = \tau \qquad (6)$$

where θ is the actual position, M is the positive definite inertia term, C is the coupling term, K is the positive definite stiffness term, F is the low-speed nonlinear dynamic friction, and τ is the input control law.

Tracking error is

$$e = \theta_d - \theta$$

Error function is defined as

$$r = \dot{e} + \Lambda e$$

where $\Lambda > 0$ is the filter coefficient, thus

$$\dot{\theta} = -r + \dot{\theta}_d + \Lambda e$$

$$\begin{aligned}
M\dot{r} &= M(\ddot{\theta}_d - \ddot{\theta} + \Lambda\dot{e}) \\
&= M(\ddot{\theta}_d + \Lambda\dot{e}) - M\ddot{\theta} \\
&= M(\ddot{\theta}_d + \Lambda\dot{e}) + C\dot{\theta} + F + K - \tau \\
&= M(\ddot{\theta}_d + \Lambda\dot{e}) - Cr + C(\dot{\theta}_d + \Lambda e) + F + K - \tau \\
&= -Cr - \tau + f
\end{aligned} \qquad (7)$$

where $f = M(\ddot{\theta}_d + \Lambda\dot{e}) + C(\dot{\theta}_d + \Lambda e) + F + K$ is the uncertain item, and associated with the vector $\boldsymbol{v}(k) = [e \quad \dot{e} \quad \theta_d \quad \dot{\theta}_d \quad \ddot{\theta}_d]$. f contains the nonlinear friction term F , which is intermittent at zero and usually unknown in practical engineering, thus it is needed to be approximated by the control law.

The control law is defined as

$$\tau = \hat{f} + k_v r \qquad (8)$$

where $\hat{f}$ is the approximation of f , k_v is the control gain.

Combining (8) and (7) yields

$$\begin{aligned}
M\dot{r} &= -Cr - \tau + f \\
&= -Cr - \hat{f} - k_v r + f \\
&= -(C + k_v)r + \tilde{f}
\end{aligned} \qquad (9)$$

where $\tilde{f} = f - \hat{f}$, that is the approximation accuracy of $\hat{f}$ to f .

Considering the convergence of tracking error, the Lyapunov function can be defined as

$$V = \frac{1}{2}Mr^2$$

The first-order derivative is

$$\dot{V} = Mr\dot{r} = r\tilde{f} - (C + k_v)r^2$$

As a result, when k_v is a constant, the stability of the control system will depend on the approximation precision $\tilde{f}$. Therefore, the identification and approximation of f ultimately affects the control performance.

3.2 THE SELF-RECURRENT WAVELET NEURAL COMPENSATION OF f

The self-recurrent wavelet neural network shown in Figure 1 is used for the self-adaptive approximation of f . The input vector is $\boldsymbol{v}(k) = [e \quad \dot{e} \quad \theta_d \quad \dot{\theta}_d \quad \ddot{\theta}_d]$, the nominal value of the network ideal weight $W_j(k)$ is defined as $\hat{W}_j(k)$, and the weight error is $\tilde{W}_j(k) = W_j(k) - \hat{W}_j(k)$. Considering the actual situation, the true value of f satisfies $f = \sum_{j=1}^{N_j} W_j(k)\cdot v_p^j(k) + \varepsilon$, where ε is the network approximation error, and $|\varepsilon| \le \varepsilon_N$.

The network nominal value output of f according to (1) is

$$\hat{f}(k) = \sum_{j=1}^{N_j} \hat{W}_j(k)\cdot v_p^j(k) \qquad (10)$$

The control law (8) is rewritten as

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$$\tau = \hat{f} + k_{\mathrm{v}} r - \beta \qquad (11)$$

where β is the robust term used to overcome the network approximation error ε, it can be designed as

$$\beta = -\varepsilon_N \operatorname{sgn}(r)$$

Combining (11) and (7) yields

$$M\dot{r} = -(C + k_{\mathrm{v}})r + \tilde{f} + \varepsilon + \beta \qquad (12)$$

The self-recurrent rate of the network nominal weight $\hat{W}_j(k)$ is defined as

$$\dot{\hat{W}}_j(k) = \lambda v_{\mathrm{p}}^j(k) r \qquad (13)$$

where $\lambda > 0$ is the weight convergence coefficient. Weights obtained by the differential equation (13) $W_j(k)$ is updated online through the position error $e(k)$ and the change rate of the position error $\dot{e}(k)$ in the k-th servo-cycle. The updating of the k-th network weights $W_j(k)$ uses only the $(k-1)$ -th servo-cycle data, and the adjustment of network weights can be done only in the k-th servo-cycle. There is no need to readjust the weights from the initial time, thus the adjustment time is greatly saved.

3.3 STABILITY ANALYSIS OF THE PROPOSED ALGORITHMS

Consider the uniform convergence of the tracking error and the network weights as the control objectives, the Lyapunov function can be redefined as

$$V(k) = \frac{1}{2} M r^2 + \frac{1}{2\lambda} \tilde{W}_j(k)^2$$

The first-order derivative is

$$\begin{aligned} \dot{V}(k) &= M r \dot{r} + \frac{1}{\lambda} \tilde{W}_j(k) \dot{\tilde{W}}_j(k) \\ &= r\tilde{f} - (C + k_{\mathrm{v}}) r^2 + r\varepsilon + r\beta \\ &\quad - (W_j(k) - \hat{W}_j(k)) v_{\mathrm{p}}^j(k) r \\ &= -(C + k_{\mathrm{v}}) r^2 + r\varepsilon + r\beta \end{aligned}$$

Since $r\varepsilon + r\beta = r\varepsilon - \varepsilon_N \operatorname{sgn}(r) r = r\varepsilon - |r|\varepsilon_N \le 0$, thus $\dot{V}(k) \le 0$, Lyapunov stability conditions can be satisfied, the tracking error and the network weights will remain UUB. Thus, the stability of the intelligent control algorithm is only related to the selection of Λ, k_{v} and λ, and independent of the system parameters, thus it is robust. In accordance with the above algorithm, the position control system block based on the friction compensation is designed as shown in Figure 2.

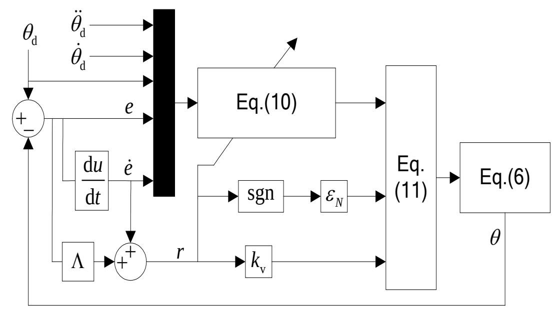


Figure 2 Self-Recurrent Wavelet Neural Friction Compensation Control System Block Diagram

4. EXPERIMENTAL RESULTS

Position control experiments are carried out under the low-speed conditions at a robot joint shown in Figure 3. The host computer is industrial PC, the hypogynous machine is Turbo PMAC servo card, MicroE2000 circular grating measures the actual joint position θ, CYB torque sensor measure the output torque, and CF-2 magnetic powder brake offer dummy load.

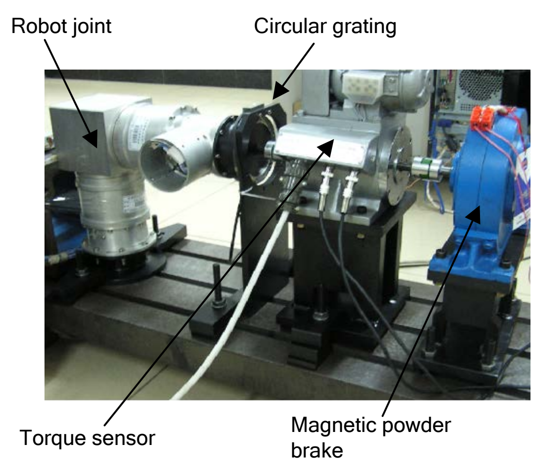
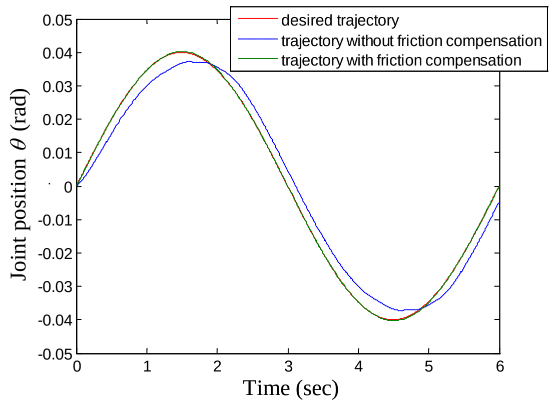


Figure 3 Robot Joint Position Control Experiment Bench

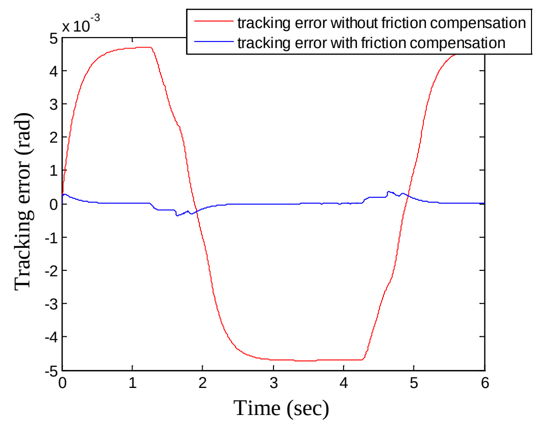
The expectation trajectory is given as $\theta_d = 0.05 \times \sin(2\pi / 6 \cdot t)\text{rad}$, namely the sine function of the amplitude for 0.05rad, cycle for 6s. Without detecting system parameters, two position tracking experiments are employed. The first experiment is done by debugging control gain $\Lambda = 5$ and $k_v = 40$ to make position tracking error reduced into $4.8 \times 10^{-3}\text{rad}$ bounded range. The second experiment is performed on the basis of the control gain $\Lambda = 5$ and $k_v = 40$, and then the self-recurrent wavelet neural compensation algorithm shown in Figure 1 and Figure 2 is introduced. The neurons number of the regression layer is $N_i = 2$, the neurons number in the product layer is $N_j = 2$, the initial value of the network nominal weight $\hat{W}_j(k)$ are all set to be zero, weight convergence coefficient is $\lambda = 1300$ in (13).

The response curves of the two experiments are shown in Figure 4 for a comparison. (a) shows the position tracking results with and without the friction compensation, one can see that there is a clear phase lag and slightly flat-topped phenomenon of position tracking before compensating friction, the tracking performance is greatly improved after using self-recurrent wavelet neural network for friction compensation. The contrast curves of tracking error can be obtained by (b), the error peak from $4.8 \times 10^{-3}\text{rad}$ to $3.8 \times 10^{-4}\text{rad}$, improved by about 12.6 times. (c) shows the output torque of the controller is maintained within a smaller range of variation with and without friction compensation, which indicates the friction compensation does not consume too much energy, and this method can save energy if it is compared with conventional high gain friction compensation. Furthermore, the boundedness of network weights in (d) also verifies the above conclusion.

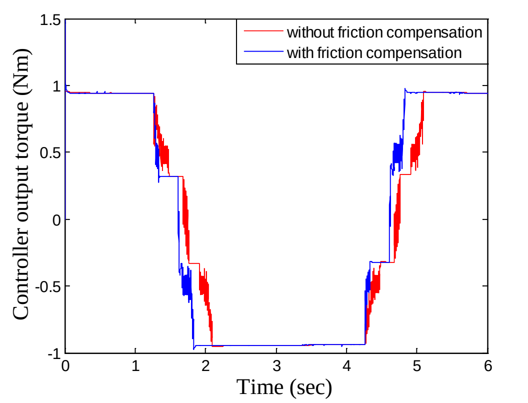
The above analysis shows that the proposed self-recurrent wavelet neural network compensation algorithm not only do not need to predict the dynamic model parameters, but also only need one state variable, namely the actual positon. The complex nonlinear friction is approximated by the proposed network with a small number of neurons and simple weights iterative algorithm. Compared with the existing neural networks, such as BP, RBFN, Gauss, etc., it has several advantages, namely, the simple topological structure, small scale, easily realized, and high identification and approximation precision.



(a) Position Tracking Results



(b) Position Tracking Error



(c) Controller Output Torque

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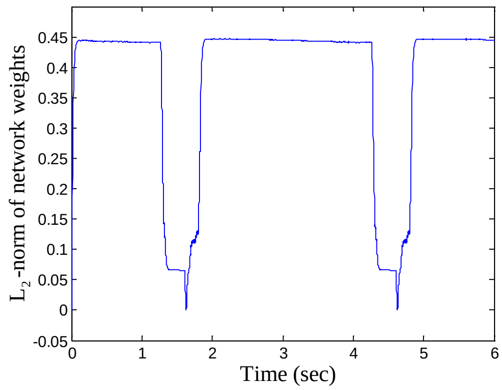

(d) L_2 Norm Of Network Weights

Figure 4 Experimental Result

5. CONCLUSION

The self-recurrent wavelet neural network has gradually refined description characterization of mutant function, and there is no requirement about the continuity of the function to be approximated. The self-feedback function of the network makes itself has a memory function, and it can map the dynamic characteristics of the mutation, thus it is suitable for approaching the discontinuous nonlinear dynamic friction at zero. There is no need to artificially separate zero for dynamic nonlinear friction function. Form the experimental results in this article, one can see that: for the low-speed position-servo system, the position tracking accuracy can be greatly improved just only by introducing the proposed self-recurrent wavelet neural network compensation algorithm on the basis of the conventional controller.

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