Research on low-speed performance of continuous rotary electro-hydraulic servo motor based on robust control with Adaboost prediction

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Abstract: In order to improve the robustness and low-speed performance of continuous rotary electro-hydraulic servo system under influences of dynamic uncertainties, parametric perturbation, friction, other non-linear properties, and uncertainties, the robust control strategy was proposed with Adaboost prediction. Firstly, basing on the system mathematic model, the model with structured uncertainty and generalised state equation was established with parametric perturbation and external disturbances, and then the robust controller was developed by adopting $H_\infty$ theory. Furthermore, Adaboost algorithm based on radial basis function (RBF) neural network was applied to design the system feedback mechanism, so the multiple weak neural network learners were obtained by using Adaboost algorithm to train system actual output and input. Also, these weak neural network learners constituted a strong learner to predict the electro-hydraulic servo system output and calculate the predictive error so as to adjust the system robust control output, so the real-time control was carried out by the robust controller. Some comparative simulated results are obtained to verify the proposed controller guarantees performances of low speed, tracking accuracy, and ability of anti-interference, which greatly expands the band of frequency response and improve the system robustness.

1 Introduction

With the rapid development of aeronautics and astronautics technology, it becomes the research hotspots in aerospace field whether the performance of navigation and guidance equipment can satisfy the requirements of precise positioning and auto tracking. The hydraulic flight simulation turntable could reproduce the aircraft's dynamics authentically, and continuous rotary electro-hydraulic servo motor as the core equipment is usually used to drive the simulation turntable and also possesses the characteristics of ultra-low speed, high precision, and wide speed regulation. However, there are some non-linearities and uncertainties, friction, and leakage, and other factors existing in electro-hydraulic servo system, which really degrades the system tracking performance in the absence of the system accurate mathematic model. Therefore, the research concentration on control field is to design a controller, which can make the electro-hydraulic servo system with non-linearities and uncertainties also yield to high-performance requirements [1, 2].

The compound control method based on $H_\infty$ mixed sensitivity is employed to restrain disturbances and effects of uncertainties existing in continuous rotary motor electro-hydraulic servo system, which just reduces effects of system non-linearities; however, the control effect on parametric uncertainties is unobvious [3]. The large extent of model uncertainties, including parametric uncertainties and uncertain non-linearities which are widely discussed in this area, and an adaptive robust control theory is employed for hydraulic actuator, load simulator, and suspension system [4–6], which makes the system to achieve requirements of tracking accuracy and response velocity in the presence of both parametric uncertainties and uncertain non-linearities. In order to compensate influences caused by parametric uncertainties and uncertain non-linearities and reduce the amplitude of system buff, a non-linear integral method about sliding mode robust control based on radial basis function (RBF) neural network is proposed by Han et al. [7], and lately, simulation verifies the effectiveness of this controller.

At present, in order to improve the system tracking accuracy and realise the real-time feedback, predictive control, the theory of predictive sliding mode control, chaotic predictive theory of neural network, and adaptive predictive method are adopted to servo system [8–10], in which the structure of general predictive algorithm is complicated and the predictive model is difficult to be established. Meanwhile, the neural network algorithm has the strength of high-non-linear fitting and the weakness of low generalisation. Besides, it is easy to fall into the local optimal, the prediction accuracy cannot achieve requirements of the electro-hydraulic servo system.

The Adaboost algorithm of machine learning is to solve the classification and regression problem. It is used to train multi-weak learners, and assign weights to each weak learner, then boost multi-weak learners into a strong one with abilities of high generalisation and non-linear reflecting, which can eliminate the over-fitting phenomenon effectively [11, 12]. Nowadays, the algorithm is widely employed for face recognition, short-term wind speed prediction, furnace temperature, fault diagnosis, and others [13–17].

When these problems are considered such as parametric perturbation, external interference, model uncertainties, non-linearities, and these weaknesses of predictive algorithm including complicated structure and lower control accuracy, the robust control method based on Adaboost prediction is proposed. By adopting the linear fraction transformation about parameters with perturbation to obtain the structural uncertainty matrix, and building the linear uncertain generalised state equation of system, the $H_\infty$ robust controller is constructed by robust control theory.

To improve the generalisation ability and prediction accuracy of the learner, the proposal here regards the system output obtained by robust controller as feedback to the Adaboost learner adopting RBF neural network regression model. The core focus is to train the output feedback so as to get different weak learners, namely the RBF neural network regression models, and then boost multi-weak learners into a strong one according to weight distribution of each weak learner. Therefore, in order to suppress the parametric disturbances, reduce influences of uncertain factors, and improve
2 Establishment of mathematical model

2.1 Linearisation flow equation of servo valve port

\[ Q_h(s) = K_s X_p(s) - K_p L(s) \]  
(1)

where \( Q_h \) is the load flow of hydraulic servo motor (m³/s); \( K_s \) the valve port's flow gain (m³/s); \( X_p \) the servo valve spool displacement (m); \( K_p \) the servo valve's flow-pressure coefficient (Pa/m); \( L \) the load pressure (Pa).

2.2 Load flow continuity equation of hydraulic motor

The load flow of the hydraulic motor is composed of three parts, that is, the flow required for normal working, the flow of internal and external leakage caused by external disturbances and self-friction, and additional flow generated by the compressed oil, which is defined as follows:

\[ Q_h(s) = D_m \theta(s) s + C_{im} P_L(s) + \frac{V_1}{4\beta_c} P_L(s) \]  
(2)

where \( D_m \) is the radian discharge capacity of motor (m³/rad); \( \theta \) the angle displacement of the hydraulic motor (rad); \( C_{im} \) the total leakage coefficient of the hydraulic motor (m³/(sPa)); \( V_1 \) the total volume including the hydraulic motor, servo-valve chamber, and the connected pipelines (m³); \( \beta_c \) the effective volume elastic modulus of the oil (Pa).

2.3 Torque balance equation of motor system

According to Newton's second law, the equilibrium equation between the sum of the torques required for the slewing motor to operate normally and external load torque can be expressed as follows:

\[ D_m P_L(s) = J\dot{\theta}(s) + B_0 \theta(s)s + G \theta(s) + T_L(s) \]  
(3)

where \( J \) is the total equivalent rotary inertia caused by hydraulic motor and its load (kg m²); \( B_0 \) the viscous damping coefficient (Nm/(rad/s)); \( G \) the elastic stiffness of the load (Nm/rad); \( T_L \) the arbitrary external load torque applied to the motor shaft (Nm).

2.4 Valve-controlled motor power system transfer function

The output angular displacement \( \theta(s) \) of the continuous rotary motor is composed of the displacement \( X_p(s) \) of the servo valve spool during motor operation and the displacement of the motor under external friction interference \( T_L(s) \). \( \theta(s) \) can be obtained by (1)–(3) (see (4)) where \( K_w \) is the total flow pressure coefficient of valve control motor (m³/s(Pa)); \( K_m \) is the control system transfer function block diagram.

Considering the actual connection situation of the continuous rotary motor, it is assumed that the external load is rigidly connected to the motor, so \( G = 0 \).

Also, \( (B_0K_c/D_m) \ll 1 \). So (4) can be simplified

\[ \theta(s) = \frac{(K_c/D_m)X_p(s) - (K_w/D_m)(1 + (V_1/4\beta_c K_w))T_L(s)}{(JV_1/4\beta_c D_m)s^3 + ((J/\omega_b K_c/D_m) + (B_0V_1/4\beta_c D_m)s^2 + (1 + (B_0K_c/D_m) + (GV_1/4\beta_c D_m)s) + (K_{cw}/D_m)} \]  
(5)

where \( \omega_b \) is the undamped natural frequency of hydraulic pressure (rad/s), \( \omega_b = \sqrt{4\beta_c D_m/JV_1} \); \( \zeta_h \) the hydraulic damping ratio, \( \zeta_h = (K_c/D_m)\sqrt{4\beta_c JV_1} + (B_0/4D_m)\sqrt{4\beta_c JV_1} \).

2.5 Electrohydraulic servo valve transfer function

In the process of establishing the transfer function of the electro-hydraulic servo valve, ignoring the influences of electro-hydraulic servo valve on the control system, it is simplified into a proportional link

\[ G_{sv}(s) = \frac{Q_h(s)}{L(s)} = K_{sv} \]  
(6)

where \( K_{sv} \) is the no-load flow gain (m³/(sA)); \( Q_h \) the no-load flow of motor (m³/s).

2.6 Servo amplifier transfer function

As the frequency band of servo amplifier was significantly higher than the hydraulic natural frequency, its dynamic influences on the system can be ignored when designing the continuous rotary electro-hydraulic servo system. So, the servo amplification step can be simplified as a proportional link

\[ \frac{I(s)}{U(s)} = K_a \]  
(7)

where \( K_a \) is the servo amplifier gain (A/V).

2.7 System transfer function of continuous rotary electro-hydraulic servo motor

The continuous rotary motor's transfer function block diagram can be obtained by (1)–(7), as shown in Fig. 1. Where \( \theta(s) \) is the input signal of continuous rotary electro-hydraulic servo system, \( \dot{\theta}(s) \) is the output signal of continuous rotary electro-hydraulic servo system, \( K_1 \) is the main controller transfer function, and \( T_L(s) \) is the friction torque. So, \( T_L(s) = 60 + 6\sin(4\pi t) \) is taken as the simulated torque for frictional disturbance [20].

Thus, the open-loop transfer function can be obtained as follows:

\[ G_L(s) = \frac{K_2 \omega_b^2}{s^2 + 2\omega_b\xi h s + \omega_b^2} \]  
(8)

where \( K \) is the open-loop gain of the system, \( K = (K_1K_{sv}/D_m) \).

2.8 Control system structure of continuous rotary electro-hydraulic servo motor

According to the transfer function block diagram of electro-hydraulic servo system as shown in Fig. 1, the main controller of system \( K_1 \) is designed through robust control theory in this paper. The system satisfies requirements of robust performance under...
these influences of non-linear factors such as parametric perturbation, friction, leakage, and external disturbances.

However, the current output of robust control system is just adjusted by error value of the last time, which does not have the characteristics of real-time control, and the control precision is not high. To overcome this defect, Adaboost algorithm with strong fitting and high generalisation ability is used as the feedback mechanism to learn the output of system and feed back to the robust controller in time. Its characteristics are to train and predict the multi-step output and input value of continuous rotary electro-hydraulic servo system, which has strong prediction ability and high precision, and can realise real-time control. The control frame diagram is shown in Fig. 2.

3 Robust controller design

$H_{\infty}$ control theory mainly researched on anti-interference control and model uncertainties. In general, continuous rotary motor electro-hydraulic servo system is subjected to effects of parametric uncertainties, such as the variations of system parameters and external uncertain non-linearities, so the control problem of system can be transformed into standard problem of robust control.

3.1 Establishment of system uncertain model

Taking the transfer function of electro-hydraulic servo valve as proportional link, and the friction torque of electro-hydraulic position servo system of the continuous rotary motor is regarded as external disturbance torque, so the linearised flow equation for the valve port of electro-hydraulic servo valve is defined as

$$Q_{\text{m}} = K_{\text{sv}}x_{\text{c}} + K_{\text{sv}}x_{\text{f}}$$

where $u$ is the control input of servo amplifier.

The equivalent block diagram of continuous rotary motor electro-hydraulic servo system can be obtained by (1)–(9) as shown in Fig. 3.

Where the uncertain parameters of system are bulk modulus $\beta_{\text{c}}$, leakage coefficient $K_{\text{ce}}$, and viscosity coefficient $B_{\text{in}}$, and $G = 0$, the

radian discharge capacity of motor $D_{\text{m}}$, the total volume $V_{\text{c}}$ of the hydraulic motor, servo-valve chamber, and the connected pipeline are all related to the motor structure, so it is supposed that $V_{\text{c}}$ is constant

So, these uncertain parameters can be written as follows:

$$\frac{4\beta_{\text{c}}K_{\text{sv}}K_{\text{a}}}{V_{\text{c}}} = a$$

$$\frac{K_{\text{sv}}}{K_{\text{a}}} = b$$

$$D_{\text{m}} = c$$

It is supposed that

$$a = \hat{a}(1 + P_{\text{a}}\delta_{a})$$

$$b = \hat{b}(1 + P_{\text{b}}\delta_{b})$$

$$c = \hat{c}(1 + P_{\text{c}}\delta_{c})$$

where $\hat{a}, \hat{b}, \hat{c}$ are the nominal value of uncertain parameters $a, b, c$, respectively; $P_{\text{a}}, P_{\text{b}}, P_{\text{c}} = 2\%$ the disturbance quantity of parameters; $-1 \leq \delta_{a}, \delta_{b}, \delta_{c} \leq 1$ the uncertainty of parameters.

Especially, these matrixes about uncertain parameters $a, b, c$ are given by the below equation

$$M_{a} = \begin{bmatrix} 0 & -\hat{a} \\ \hat{a} & a \end{bmatrix}$$

$$M_{b} = \begin{bmatrix} 0 & -\hat{b} \\ \hat{b} & b \end{bmatrix}$$

$$M_{c} = \begin{bmatrix} 0 & -\hat{c} \\ \hat{c} & c \end{bmatrix}$$

So, (10) can be expressed as follows:

$$a = \hat{a}(1 + P_{\text{a}}\delta_{a})$$

$$b = \hat{b}(1 + P_{\text{b}}\delta_{b})$$

$$c = \hat{c}(1 + P_{\text{c}}\delta_{c})$$

where $M_{a11} = M_{b11} = M_{c11} = 0$.

Based on (12), by using additive uncertainty modelling, Fig. 3 is transformed into another model structure, as shown in Fig. 4.

In Fig. 4, the inputs of $\delta_{a}, \delta_{b}, \delta_{c}$ (uncertainty of parameters) are $y_{\text{a}}, y_{\text{b}}, y_{\text{c}}$, and the outputs are $u_{\text{a}}, u_{\text{b}}, u_{\text{c}}$, respectively. So, Fig. 4 is described as follows:

$$\begin{bmatrix} x_{1} = y_{1} = \theta \\ x_{2} = \hat{\theta} \\ x_{3} = x_{2} - G_{x_{1}} - \frac{\hat{b}}{J_{x}} + \hat{P}_{L} - P_{\text{a}}u_{\text{a}} - T_{L} \\ P_{L} = P_{\text{a}}\theta_{\text{a}} + \hat{a}(u - D_{\text{m}}\theta_{\text{m}} - \nu_{\text{b}}) \\ y_{a} = \nu_{\text{a}}\hat{\theta}_{\text{a}} + \hat{a}(u - D_{\text{m}}\theta_{\text{m}} - \nu_{\text{b}}) \\ y_{b} = P_{L}\hat{b} \\ \gamma_{c} = c\theta_{\text{m}} \\ u_{\text{a}} = \delta_{a}\gamma_{c} \\ u_{\text{b}} = \delta_{b}\gamma_{c} \\ u_{\text{c}} = \delta_{c}\gamma_{c} \end{bmatrix}$$

$\Delta$ represents the transforming matrix between input and output of parametric perturbation, so it is defined as

$$\Delta = \begin{bmatrix} \delta_{a} \\ \delta_{b} \\ \delta_{c} \end{bmatrix}$$

satisfying $|\Delta| < 1$. Based on Fig. 4 and (14), the general closed-loop system of continuous rotary electro-hydraulic servo motor with structure uncertainties is established as shown in Fig. 5.
3.2 Controller design and simulation

The continuous rotary electric–hydraulic servo motor is developed by laboratory, whose radical discharge capacity is $D_m = 1.59 \times 10^{-3}$ m$^3$/rad, the pressure of oil source is 12 MPa, the total effective volume of motor, servo valve, and connecting tubes is $V_1 = 1.21 \times 10^{-3}$ m$^3$, the load inertia is $J_L = 10$ kgm$^2$, the volume elastic modulus of oil system is $E_o = 7 \times 10^7$ N/m$^2$, the natural frequency of the hydraulic servo system is $\omega_n = 92.63$ rad/s, and $\xi_b = 0.1$. The electric–hydraulic servo valve's type is SF106-10 whose main technical parameters are that the rated pressure is $P_s = 16$ MPa, the rated current is $40$ mA, $\xi_w$ is 0.6, the flow gain is $K_w = 0.04941$ m$^3$/sA, $\pm 10$ V is the saturation value of the servo amplifier control voltage, so its gain is $K_e = 0.0008$ A/V.

As the saturation value of the servo amplifier control voltage is $\pm 10$ V, so the weight function of input is $W_u = 0.1$. Also, the weight function of system properties $W_p$ can be chosen as follows:

$$W_p = 0.85 * \frac{1.13s^5 + 8s + 3}{1.1s^3 + 0.9s + 0.1}$$

(15)

So, the nominal model of the continuous rotary motor $G_{mds}$ is given by the below equation (see (16)) The open-loop transfer function of the continuous rotary motor can be obtained as follows:

$$G_K = \frac{1454}{s^3 + 550.5s^2 + 5850s}$$

(17)

The nominal model and weighting function of continuous rotary electro-hydraulic servo motor are connected by ‘input to’ command of Matlab, and the general solved open-loop system is established, which includes the six inputs and outputs, respectively, as shown in Fig. 6.

The system $H_\infty$ robust controller is solved by using the ‘hinfsyn’ command based on Fig. 6. Furthermore, the third-order controller can be designed by reducing the order

$$K = \frac{197320(s + 16.2)(s + 0.001929)}{(s + 30870)(s + 34.56)s + 0.1333}$$

(18)

On the other hand, in order to verify whether the designed robust controller satisfies requirements of robust performance, the system nominal model $G_{mds}$ with parametric uncertainties should satisfy the below equation

$$\left\| W_p(1 + G_{mds}K)^{-1} \right\|_\infty < 1$$

(19)

Equation (19) can be transformed into the below equation

$$\sigma(S(j\omega)) < \sigma(W_p^{-1}(j\omega))$$

(20)

where $S$ is sensitivity function, namely $S = 1 + G_{mds}K$, and $\sigma(S(j\omega))$ is the largest singular value of $S$. As Figs. 7 and 8 show, with the frequency changing, the singular of electro-hydraulic servo system with $H_\infty$ controller $K$ is always $\leq 1$, and the singular of sensitivity function $S$ is less than the singular of weight function's reciprocal $W_p^{-1}$. Above of them illustrate the proposed controller satisfies the requirements of (19), so the proposed controller satisfies the requirements of system robust stability [21].

On the other hand, the control system's ability of restraining disturbance input can be verified by simulation when the parametric perturbation are $\Delta = 0$ and $\Delta = 0.9$ respectively. The simulated result is shown in Fig. 9, in which the dash-dot line represents the simulation results of $\Delta = 0$ and the solid line represents $\Delta = 0.9$.

$$G_{mds} = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & -543 & 1.59 \times 10^{-4} & 0 & 0 & -0.02 & -1 & 0 \\
0 & -1.454 \times 10^{-3} & -16.198 & 0.02 & -1.829 \times 10^{-5} & 0 & 9.147 \times 10^{-7} & 0 \\
0 & -1.454 \times 10^{-3} & -16.198 & 0 & -1.829 \times 10^{-5} & 0 & 9.147 \times 10^{-7} & 0 \\
0 & 0 & 1.771 \times 10^{-7} & 0 & 0 & 0 & 0 & 0 \\
0 & 543 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

(16)
Fig. 8 Singular value contrast diagram

Fig. 9 Step disturbance response of the system

Fig. 10 Bode diagram with robust controller

In addition, the Bode diagram of electro-hydraulic servo system with a robust controller is analysed. Fig. 10 shows that the gain margin of the system is 67.1 dB and the phase margin is 127.6°, which indicates that the closed-loop system is stable and has better ability of inhibiting disturbance and strong robustness.

4 Design of Adaboost learner based on RBF neural network

This paper adopts RBF neural network regression model as learner of Adaboost. RBF neural network has these characteristics of high non-linear fitting, simple structure, and its classification ability and learning speed are better than BP neural network, which can overcome limitations of the local minimum point. The construct of network is selected as 2-4-1, and Gaussian transfer function is selected as activation function of the hidden layer. The maximum learning times is 10,000, the learning rate is 0.1, the mean square error is 0.00001, and the dispersion constant is 1.

The algorithm of Adaboost based on RBF neural network illustrates that every sample of training set has the same weight at the beginning of training, then every sample is studied to obtain multi-trained network learners by applying RBF neural network, later the predictive error is calculated between the output of sample and one of the trained networks. So, the weight of trained learner and weights of every training sample of training set are determined. Then the learning process is carried out $T$ times again in the new sample distribution, and $T$ basic weak learners and a weight vector can be obtained, so that a strong learner can be obtained by linear combination eventually.

The concrete steps of this algorithm are as follows.

Step (1): Based on the control block diagram as shown in Fig. 2, the system output of robust control is considered as a time series, using $n$ output values of the past time to predict the output values of the next time and then selecting ten couples of system outputs and inputs to get a training set. Namely $(r_1, y_1), (r_2, y_2), \ldots, (r_{10}, y_{10}), r_j \in R, y_j \in Y$, in which $R, Y$ represent the input and output of system.

Step (2): The training set obtained from step (1) is divided into five data segments with certain length of 5, and every data segment denotes a training sample, then the weights of five samples are initialised ($D_t(i) = 1/5$), $D_t(i)$ is the weight of the sample $i$ in the $t$ iteration.

Step (3): The samples of training set should be conducted normalisation before using RBF neural network. In the distribution of initial weights, selecting a trained neural network net, randomly, that is weak learner, in which $t$ represents the trained network of the $t$ times.

Step (4): The mean square errors $mse_t(i)$ of weak learner net, are calculated, where $i$ denotes the $i$ sample's mean square errors in the process of $t$ times’ training, so the equation can be given by $E(t) = \sum_{i=1}^{n} D_t(i)^*mse_t(i)$, in which $E(t)$ is the sum of the product of the mean square error and the weight of each sample.

Step (5): At $t$ times, by updating the samples’ weights and calculating $\beta_t(i) = (E(t)/(1-E(t)))$, and the trained sample's weight of weak learner is expressed as $W(i) = 0.5*\ln(1/\beta_t(i))$, and the samples’ weight is $D_t+1(i) = D_t(i)*\beta_t(i)*\exp(1 - (mse_t(i)/\max[mse_t(i)])$.

Step (6): Switch back to step (3) and proceed to the next iteration until the five iteration.

Step (7): At last, the strong learner can be obtained by combining the trained weak learners, which is expressed as $H(t) = \sum_{i=1}^{T} W(i)*net_i$.

In addition, $D_{t+1}(i)$ is the weight of new samples and the sum of every sample’ weight must be equal to 1, so it is requested to conduct normalisation by the following equation

$$D_{t+1}(i) = \frac{D_{t+1}(i)}{\sum_{i=1}^{n} D_{t+1}(i)}$$

The flow diagram of Adaboost predictive algorithm based on RBF neural network is shown in Fig. 11.

5 Simulation research

According to the algorithm flow diagram, algorithm programming is performed by using S function. Then according to the control structure block diagram of the continuous rotary electro-hydraulic servo system as shown in Fig. 2, the robust controller with Adaboost algorithm is designed in this paper, and later the model of control system is established in Simulink.

5.1 Study on simulation of slope response

In order to study the low-speed performance of system, the slope input signal of 0.001$^\circ$/s is adopted. Comparing the effectiveness of the traditional PID controller with the robust controller proposed by this paper, the simulation result is shown as Fig. 12, in which Fig. 12a shows the system response curves and Fig. 12b shows the local amplification of the response curves. Curves 1 and 2 are the error bands, the solid line is the slope input signal of 0.001$^\circ$/s, the dotted line is the output response curve under the PID control, and the dash-dot line is the output response curve of robust control with Adaboost prediction.
Fig. 12 shows that the system goes to steady state gradually with low response speed and large error under the control of PID. System under the control of robust controller with Adaboost prediction has high tracking precision and frequency response and the steady-state error is eliminated well. Through comparison, it shows that the controller designed in this paper has a better super low-speed control performance compared with PID control.

Fig. 13 Response characteristic curve of sinusoidal input signal (8 Hz, 1°) (a) The whole response curves of simulation, (b) The control effect of local amplified drawing

Fig. 14 Response characteristic curve of sinusoidal input signal (10 Hz, 1°) (a) The whole response curves of simulation, (b) The control effect of local amplified drawing

Fig. 15 Response characteristic curve of sinusoidal input signal (12 Hz, 1°) (a) The whole response curves of simulation, (b) The control effect of local amplified drawing

Fig. 16 Response characteristic curve of sinusoidal input signal (14 Hz, 1°) (a) The whole response curves of simulation, (b) The control effect of local amplified drawing

5.2 Research on sinusoidal response simulation

Simulator with continuous rotary electro-hydraulic servo motor requires good performance, and the double-ten index as the specific quantitative scale means that amplitude error is <10%, and phase error is <10°. The responses of sinusoidal signal with the input amplitude of 1° and different frequencies are shown in Figs. 13–18. Figs. 13a–18a show the system response curve, and Figs. 13b–18b show the local amplification of the response curve. The solid line represents the sinusoidal input signal with different frequencies, the dash-dot line indicates the response of system under the traditional PID control, and the dotted line is the sinusoidal output response curve under the robust control with Adaboost prediction.
In summary, the robust control with Adaboost prediction has high robustness and anti-interference ability on both slope signal and sinusoidal signal. The simulation results show that this controller effectively improves the low-speed stability and tracking accuracy of continuous rotary electro-hydraulic motor. The precise control of the servo system is realised.

6 Conclusion

In this paper, the robust controller with Adaboost algorithm based on RBF neural network prediction is proposed and applied to the continuous rotary electro-hydraulic servo system. Also, the particular non-linearities, parametric perturbation, external interferences, and uncertainties were taken into account to design robust controller and realise the real-time control. The simulation results show that the proposed controller has a high tracking performance on low-speed slope signal, and high response speed on sinusoidal signal whose maximum response frequency can reach 15 Hz; meanwhile, the frequency band of system is widen. Above of all, it is demonstrated that the proposed controller can satisfy the requirements of frequency response and low-speed performance, and effectively reduce the influence of system parameters perturbation, external interference, friction, and leakage, and also have a strong robustness.

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