Article

JVC

Journal of Vibration and Control
17(13) 2007–2014

DOI: 10.1177/1077546310395972
jvc.sagepub.com
SAGE

Adaline neural network-based adaptive inverse control for an electro-hydraulic servo system

Jianjun Yao[1], Xiancheng Wang[2], Shenghai Hu[1] and Wei Fu[1]

Abstract

Based on adaptive inverse control theory, combined with neural network, neural network adaptive inverse controller is developed and applied to an electro-hydraulic servo system. The system inverse model identifier is constructed by neural network. The task is accomplished by generating a tracking error between the input command signal and the system response. The weights of the neural network are updated by the error signal in such a way that the error is minimized in the sense of mean square using (LMS) algorithm and the neural network is close to the system inverse model. The above steps make the gain of the serial connection system close to unity, realizing waveform replication function in real-time. To enhance its convergence and robustness, the normalized LMS algorithm is applied. Simulation in which nonlinear dead-zone is considered and experimental results demonstrate that the proposed control scheme is capable of tracking desired signals with high accuracy and it has good real-time performance.

Keywords

Adaptive inverse control, mean square error, neural network, normalized LMS algorithm, tracking performance

Received: 14 July 2010; accepted: 18 October 2010

1. Introduction

Hydraulic drives are widely used in such main industrial fields as aerospace, metallurgy, transportation and machine (Li, 1990). For a large-scale shaking table which needs large forces, it usually uses hydraulic power. Compared with others types of drives, hydraulic drives have many distinct advantages, such as developing a comparatively small device with a much larger torque, higher respond speed, higher stiffness and higher force-to-weight ratio. However, there are also many disadvantages in electro-hydraulic control systems (Yao et al., 2008a). For example, the highly nonlinear phenomenon (Merritt, 1967), such as friction, dead zone, fluid compressibility, the flow-pressure relationship and dead-band due to the internal leakage and hysteresis. The dynamic performance of a servo valve is influenced by operating conditions, such as supply pressure, fluid and ambient temperature, and so on.

For the control of an electro-hydraulic servo system, it is usually needed to reproduce the expected signal with high-precision requirements. For example, an electro-hydraulic shaking table usually needs to reproduce the predetermined acceleration signal. Because nonlinearities and uncertainty occur in the hydraulic system, classical control schemes, for example, PID controller, do not give satisfactory performance, so current research is focused on a nonlinear control scheme, which is a control method for adaptively changing control parameters in real time so as to achieve a desired input-output characteristics even when dynamic characteristics of the system to be controlled are changed by operating conditions and the environment. An ANN-based PID controller was developed by Yao et al.

[1]College of Mechanical and Electrical Engineering, Harbin Engineering University, Harbin, People's Republic of China
[2]Department of Electromechanical Engineering, Ningbo Institute of Technology, Zhejiang University, Ningbo, People's Republic of China

Corresponding author:
Jianjun Yao, College of Mechanical and Electrical Engineering, Harbin Engineering University, Harbin 150001, People's Republic of China
Email: travisyao@126.com

(2008b) using cerebellar model articulation controller (CMAC) neural network. It cannot compensate amplitude attenuation and phase delay caused by system dynamics. Knohland and Unbehaue, (2000) developed adaptive position control for a hydraulic system using two ANNs, one for describing the nonlinear function in the system and the other for controlling the linear part of the system. Its structure is complex and it has computation burden. Variable structure control using Lyapunov method and pole placement (Yao et al., 2006), adaptive controller combined with other control methods (Cheng and Pan, 2008; Claude et al., 2006; Lee et al., 2009; Wan et al., 2008; Zhang et al., 2008) were also designed for electro-hydraulic servo system. Those control schemes need to know the mathematical model of the original system but it is usually difficult to build its precise models. Tagawa and Kajiwara (2007) developed input reference modification technique which is a type of off-line feed-forward method, and it needed to identify the system frequency characteristics. This may cause premature collapse of the specimen, and also the convergence property can not guaranteed for the shaking test with strong nonlinear specimens (Tagawa and Kajiwara, 2007)

The adaptive inverse control is created by B Widrow in Stanford University (Widrow and Sterns, 1985). It uses a cascade controller, whose transfer function is the inverse of the plant, to realize satisfied control performance (Liu and Han, 2000). Adaptive inverse control is a well established adaptive tracking methodology, as described by Shafiq and Shafiq (2009). The control scheme has attracted the interests of many researches for several decades (Gregory, 2003; Liu and Han, 2000; Plett, 2002; Shafiq and Shafiq, 2009; Yuan et al., 2008). Wu et al. (2005) applied adaptive inverse control to an electro-hydraulic servo system with known parameters, and the weights were off-line trained.

In this paper, combined with adaptive inverse control and neural network, neural network adaptive inverse control (NN-AIC) scheme is developed for an electro-hydraulic servo system. The weights of the neural network are on-line updated by the least mean square (LMS) algorithm according to the error between the command input and the system response to make mean square error be least, and inverse controller constructed by the neural network becomes the inverse model of the system, making the system response track the command input in real-time.

2. System description

The hydraulic system shown in Figure 1 is comprised of a symmetric cylinder, a symmetric servo valve and a load force: assuming no leakage.

A mathematical model of the plant can be derived from the flow equation of the valve, the continuity equation and the force balance at the piston. The valve-flow-rate equation is nonlinear and dependent on the valve displacement from neutral. A Taylor series expansion yields (Li, 1990)

$$q_{V\mathrm{L}} = K_{\mathrm{g}} x_v - K_\rho p_{\mathrm{L}} \tag{1}$$

where K_{g} is the flow-gain coefficient and K_ρ is the flow-pressure coefficient. The load-induced pressure p_{L} is named as

$$p_{\mathrm{L}} = F_{\mathrm{L}}/A = p_{\mathrm{i}} - p_{\mathrm{o}} \tag{2}$$

where A is the effective area of piston. The oil flow can also be written as

$$q_{V\mathrm{L}} = (q_{V\mathrm{i}} + q_{V\mathrm{o}})/2 \tag{3}$$

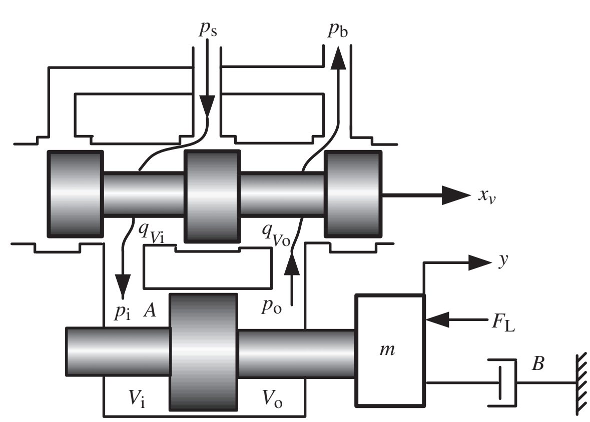
where $q_{V\mathrm{i}}$, $q_{V\mathrm{o}}$ is the input/output oil flow of the cylinder, respectively; $q_{V\mathrm{L}}$ is the load flow.

The continuity equation of the cylinder are given as

$$\dot{p}_{\mathrm{i}} = K(q_{V\mathrm{i}} - A\dot{y})/V_{\mathrm{i}} \tag{4}$$

$$\dot{p}_{\mathrm{o}} = K(A\dot{y} - q_{V\mathrm{o}})/V_{\mathrm{o}} \tag{5}$$

where $\dot{y}$ is the velocity of the piston and K is the effective bulk modulus of the hydraulic oil.



p_s — Supply pressure
p_b — Return pressure
V_{i} — Input oil volume of the cylinder
V_{o} — Output oil volume of the cylinder
x_v — Valve displacement
y — Displacement of the piston
F_{L} — Load force

Figure 1. Schematic diagram of the hydraulic system.

Combining equations (2) to (5) results in the flow continuity equation of the cylinder

$$q_{VL} = A\dot{y} + V\dot{p}_{L}/(4K) \tag{6}$$

where $V_t = V_i + V_o$ is the total oil volume of the cylinder.

The balance of the force at the sliding carriage leads to

$$Ap_{L} = m\ddot{y} + B\dot{y} + F_{L} \tag{7}$$

where m is the total mass of the piston and the load, B the equalized viscous damping coefficient, and$\ddot{y}$is the acceleration of the piston

Combining equations (1), (6) and (7) and applying the Laplace transformation to the resulting third-order differential equation results in the function (Yao, 2007)

$$Y = \frac{\frac{K_g}{A}X_v - \frac{K_\rho}{A^2}\left(1+\frac{s}{\omega_1}\right)F_L}{s\left(\frac{s^2}{\omega_h^2}+\frac{2\zeta_h}{\omega_h}s+1\right)} \tag{8}$$

where $\omega_h = \sqrt{\dfrac{4KA^2}{mV_t}}$,

$$\zeta_h = \frac{K_\rho}{A}\sqrt{\frac{Km}{V_t}} + \frac{B}{2A}\sqrt{\frac{V_t}{4Km}},$$

$$\omega_1 = 4KK_\rho/V_t.$$

In equation (8), the load force F_L is considered as an external disturbance.

3. Adaptive inverse control based on adaline neural network

Adaptive inverse control is based on the concept of dynamic inversion, but an inverse need not exist. The idea of adaptive inverse control is that control of plant dynamics can be achieved by preceding the plant with an adaptive controller whose dynamics is a type of inverse of the plant, thus satisfactory system dynamic characteristics are obtained (Liu and Han, 2000). This can be explained in Figure 2. The aim of the system is to make the system response track the command input, r. The inverse controller is adjustable, and its parameters are adjusted by an adaptive algorithm according to the error between the command and the system response, y, to minimize the error in a least-mean-square error optimal sense. When the adaptation is converged, the cascade of the inverse controller followed by the plant will have the desired tracking performance.

For a real plant, it is usually nonlinear and has uncertainties, so nonlinear dynamic inversion may be computationally intensive and precise dynamic model may not be available. This causes difficulty in the inversion of the plant using traditional methods. Artificial neural networks (ANN) has been recognized as a powerful tool which is tolerant of imprecision and uncertainty, and can facilitate the effective development of models by combining information from different sources. This technique has been used in a wide variety of applications in engineering, science, business, medicine, psychology, and other fields.

Adaline neural network has been applied successfully in many applications. An Adaline is applied here to identify the inverse of the system. The Adaline is a single-layered neural network having N inputs and a single output which is the dot product of input $\boldsymbol{x}$, and the weight vector $\boldsymbol{w}$ (shown in Figure 3, as described by Xu (1999)). The input/output relationship of the Adaline is linear at any given time. However, when its weights are adjusted on-line, the relationship between the input/output signals, as a function of time, is no

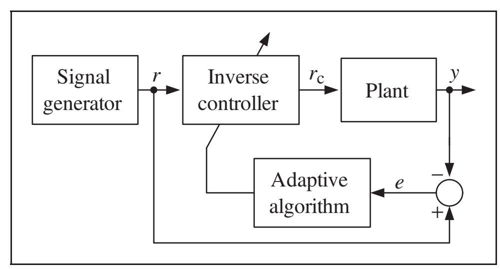


Figure 2. Adaptive inverse control.

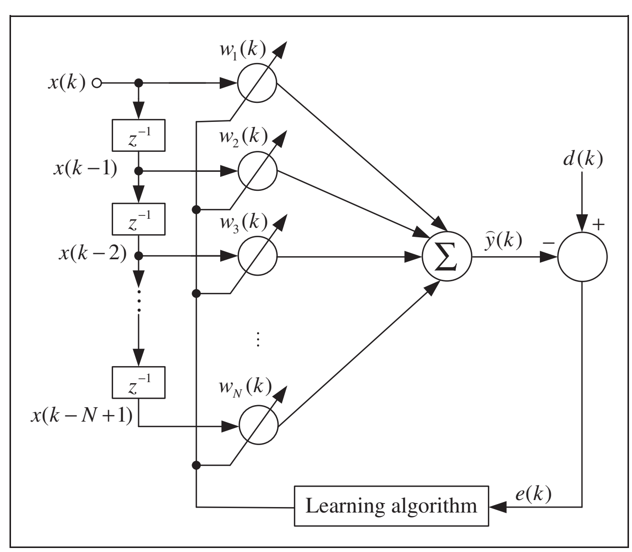


Figure 3. Adaline neural network.

longer linear. Training is the process of tuning the weights of the Adaline so that its output y_{nn} matches the desired outcome d. The main advantage of the Adaline architecture is the ability of the Adaline that can be trained on-line, eliminating the need for repetitive off-line training. Although most neural networks have the ability of on-line training, the Adaline is superior because of its simple structure and speed (Yao et al., 2006).

The weight of the Adaline is updated by the Widrow-Hoff LMS algorithm (Simon, 2002)

$$\boldsymbol{w}_{k+1} = \boldsymbol{w}_k + \alpha e(k)\boldsymbol{x}_k \tag{9}$$

$$e(k) = d(k) - y_{nn}(k) = d - \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} \tag{10}$$

Where

$$\boldsymbol{x}_k = [x(k), x(k-1), \ldots, x(k-N+1))]^{\mathrm{T}},$$
$$\boldsymbol{w}_k = \left[w_1(k), w_2(k), \ \ldots, w_N(k)\right]^{\mathrm{T}},$$

LMS algorithm, as an iterative gradient-descent algorithm, uses an estimate of the gradient on the mean-square error surface to seek the optimum weight vector at the minimum mean-square error point. The term $e(k)\boldsymbol{x}_k$ represents the estimate of the negative gradient, and the adaptation constant α determines the step size taken at each iteration along that estimated negative-gradient direction. The true negative gradient is given by the expected value of $e(k)\boldsymbol{x}_k$. If α is chosen properly, such that small steps are taken, adaptation noise due to error in the gradient estimate is averaged out. When adapting with LMS on stationary stochastic processes, the expected value of the weight vector converges to a Wiener optimal solution (Simon, 2002; Widrow and Sterns, 1985).

In the LMS algorithm, the adjustment is directly to the input $\boldsymbol{x}$. Therefore, the algorithm will suffer from a gradient noise amplification problem, when the input is large. An important limitation regarding LMS algorithm is that the selection of a certain value for the step size implies a compromise between convergence rate and final mis-adjustment. To overcome those difficulties, the normalized LMS algorithm can be used. In particular, the adjustment applied to the weight vector at iteration $k+1$ is ''normalized'' with respect to the squared Euclidean norm of the input $\boldsymbol{x}$ at iteration k, hence the term is ''normalized''. In structure terms, the normalized LMS algorithm is exactly the same as the LMS algorithm. Both algorithms are built around a transversal filter, but differ only in the way in which the weight is mechanized. The normalized LMS algorithm is a manifestation of the principle of minimal disturbance (Simon, 2002). The weight can be updated by

$$\boldsymbol{w}_{k+1} = \boldsymbol{w}_k + \tilde{\alpha}\boldsymbol{x}_k e(k)/(\|x_k\|^2+\delta) \tag{11}$$

where δ is a positive number and is used to overcome the computation problem when the input vector is very small. The normalized LMS algorithm can be considered as an LMS algorithm with a time-varying step-size parameter. Most importantly, the normalized LMS algorithm has a rate of convergence that is potentially faster than that of the traditional LMS algorithm. Its convergence has been described by Simon (2002)

Using the adaptive inverse control scheme in Figure 2 and the Adaline neural network in Figure 3, NN-AIC is developed for electro-hydraulic servo system. In NN-AIC, the input of the Adaline to estimate the inverse is

$$x_k = [r(k), r(k-1), \ldots, r(k-N+1)]^{\mathrm{T}}$$

The command input$r$is also used as the desired signal d for Adaline. The weights are updated by equation (11) according to error between the command and the system response. The output of the neural network, which is $r_c(k) = \boldsymbol{w}_k^{\mathrm{T}}\boldsymbol{x}_k$, is used as the input to the electro-hydraulic servo system. The Adaline is driven to estimate the system inverse such that the system replicates the command.

4. Simulation results

In order to illustrate the efficiency and validity of the proposed NN-AIC approach, a valve-controlled cylinder hydraulic system of a 6 degrees-of-freedom shaking table is taken for a simulation example. Assuming $F_L = 0$. Identification of the real plant gives the transfer function

$$G(s) = \frac{73.339}{s(s^2/156.8^2 + 0.305s/156.8 + 1)}$$

During simulation, a nonlinear dead-zone portrayed in Figure 4 is added to the input of the linear model.

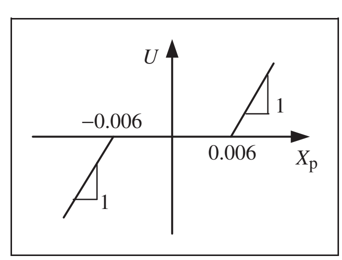


Figure 4. Nonlinear dead-zone.

For NN-AIC, $N = 6$, $\tilde{\alpha} = 0.02$, $\delta = 5 \times 10^{-6}$. The initial values of the weights are all set to zeros.

When the command input is $0.1 \sin 20\pi t$ m, the system response is shown in Figure 5. Clearly, there are amplitude attenuation and phase delay in the system response. Figure 6 is the system response after using the proposed with Figure 5, phase lag and magnitude attenuation are all three periods of the fundamental frequency.

Figure 7 is the system response corresponding to a sine sweep signal whose initial frequency, target frequency, target time,amplitude are 0.5 Hz, 5 Hz, 5 s and 50 mm, respectively, while Figure 8 is its response after using NN-AIC method. Figure 9 is its error curve after using NN-AIC plotted with the error before using the proposed scheme.

From Figure 9, it can be seen that the error before using NN-AIC becomes more serious as the input frequency increased. This is the result of the increase of

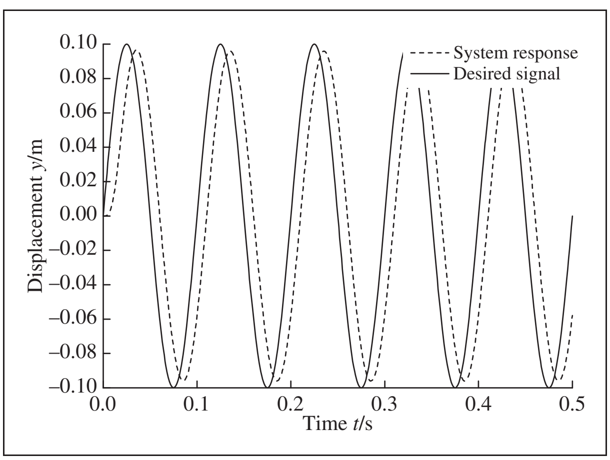


Figure 5. System sinusoidal response before using NN-AIC.

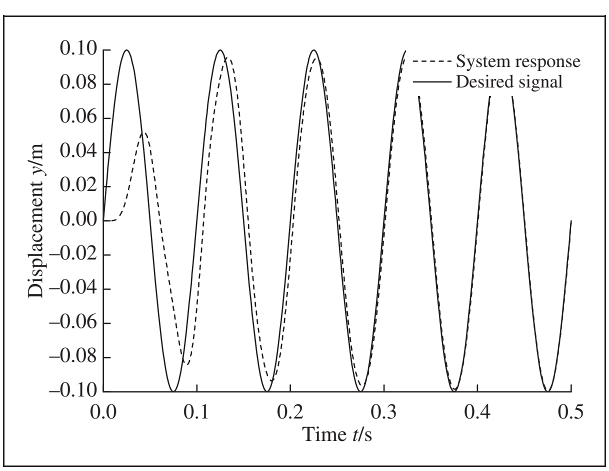


Figure 6. System sinusoidal response after using NN-AIC.

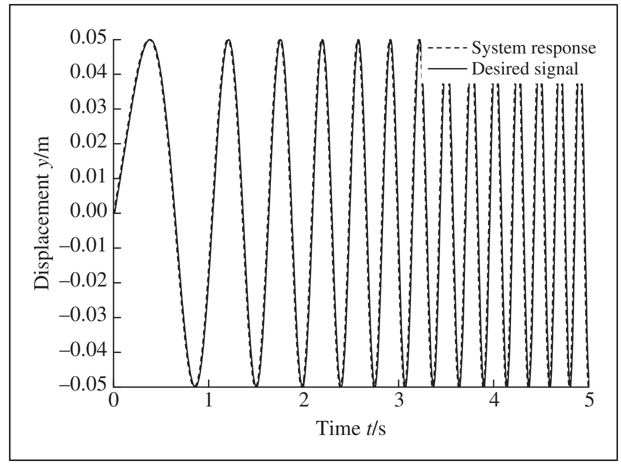


Figure 7. System sine sweep response before using NN-AIC.

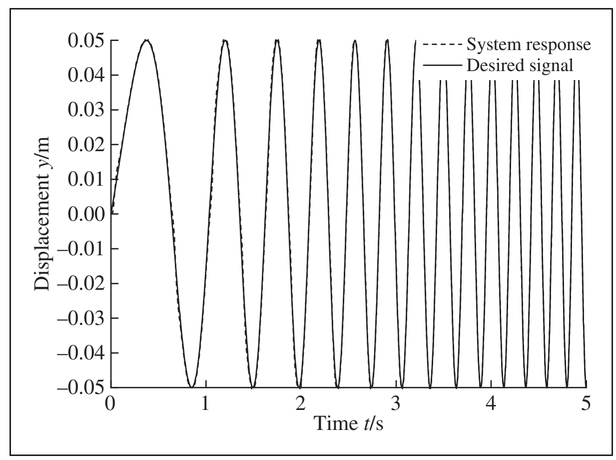


Figure 8. System sine sweep response after using NN-AIC.

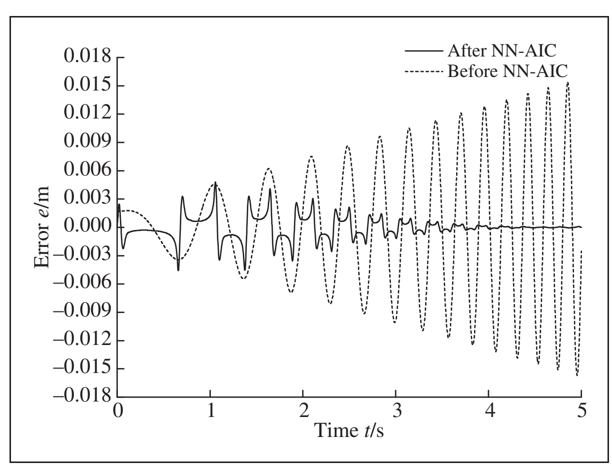


Figure 9. Error curve.

phase lag and amplitude attenuation of the response with the increase of the input frequency. The error after using NN-AIC is diminished with the control action of NN-AIC.

From the system response, both sine and sine sweep signal, the system can precisely track the command input with NN-AIC.

5. Experimental results

The electro-hydraulic servo system used to validate the proposed control scheme is an asymmetric cylinder controlled by a MOOG D792 servo valve, which is a three-stage servo valve. System parameters are shown in Table 1. For NN-AIC, $N = 6$, $\tilde{\alpha} = 0.02$, $\delta = 5 \times 10^{-6}$. The initial values of the weights are all set to zeros.

Figures 10 and 11 are the responses when the input is $0.1\sin(2\pi t)$ m. From Figure 10, it can be seen that there are phase delay and amplitude attenuation. Figure 11 shows that the system response tracks the desired input asymptotically. So he proposed scheme can make the system track the command both in phase and in amplitude with fast speed and high precision.

Figure 12 is the system response when the input signal is $0.08\sin(\pi t) + 0.06\sin(2\pi t) + 0.04\sin(3.4\pi t)$ m. For a hydraulic servo system, it usually has low frequency. When the input frequency is increased, the

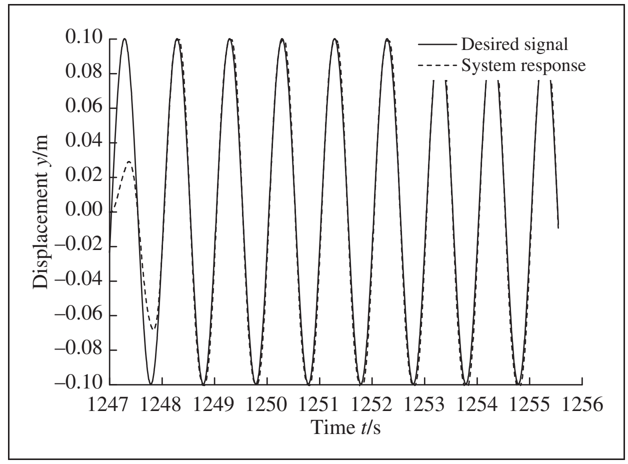


Figure 11. System sinusoidal response after NN-AIC.

Table 1. System parameters

Item	Value	Unit
Cylinder stroke	1350	mm
Cylinder piston	Φ125	mm
Cylinder rod	Φ90	mm
Oil supply pressure	8	MPa
External load	6500	kg
Sample time	2	ms

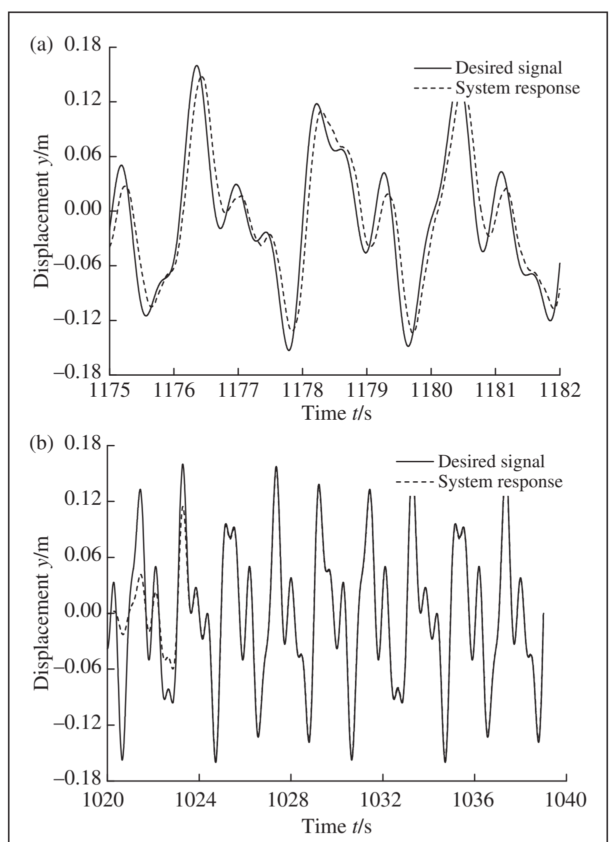


Figure 12. System sinusoidal response with hybrid frequencies. (a) Before NN-AIC (b) After NN-AIC.

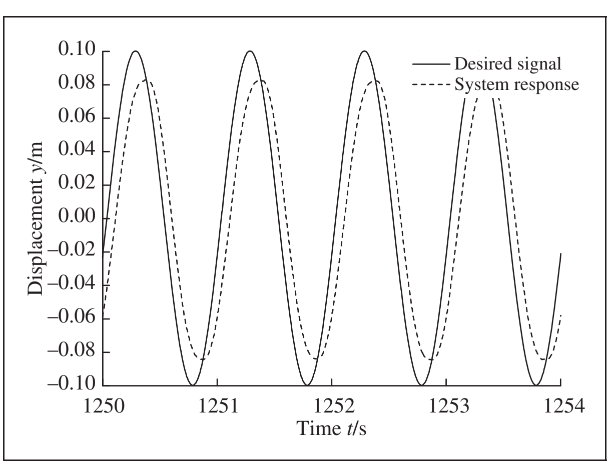


Figure 10. System sinusoidal response before NN-AIC.

tracking performance will become worse. This is depended on the system frequency characteristics. The first figure in Figure 12 shows the unsatisfied tracking performance excited by a hybrid frequencies signal. The second figure shows when the proposed NN-AIC scheme is applied to the system, the system can follow the command input with high precision and good efficiency, though the input has hybrid frequencies.

6. Conclusions

To improve the tracking performance for an electro-hydraulic servo system, ANN-based adaptive inverse control is developed. Using the adaptive inverse control theory, an Adaline neural network is applied to estimate the inverse of the system. Its weights are updated on-line in real time by the normalized LMS algorithm according to the error between the command and the system response. When the adaptation is converged, the error is gradually minimized in a least-mean-square error optimal sense, and the gain of the serial connection system is close to unity.

The simulation is performed with a hydraulic system of an electro-hydraulic servo shaking table, and non-linear dead-zone is added into the simulation. Sine signal with single frequency and sine sweep signal with variable frequencies are used to validate the proposed control scheme. The results demonstrate that the developed control method can efficiently improve the tracking performance.

To further testify its efficiency and validity, experiments are also done on an electro-hydraulic servo system. Sinusoidal responses with both single frequency and hybrid frequencies show the system can asymptotically track the command input with high precision after using NN-AIC scheme.

The model in the system description is a hydraulic system with a symmetric cylinder controlled by a symmetric servo valve, and the cylinder for the experimentation is an asymmetric style. However, when the proposed control scheme is applied for the hydraulic systems with different style cylinders, the control principle is the same. From the simulation and experimentation results, it can be seen that the NN-AIC can achieve satisfied control performance both for symmetric cylinder and for asymmetric cylinder, thus the control scheme has good applicability.

The proposed control scheme has good real-time performance, and does not need to know the priori knowledge of the system. For the control scheme, the length of the weight has great impaction on the control performance. The tracking performance will be improved with the increase of weight at the cost of complexity and computation burden. So in real application, the weight length should be selected according to the tracking performance and the system software and hardware environment.

Acknowledgements

The author is grateful for the support of National Natural Science Foundation of China (No. 50905037), the Specialized Research Fund for the Doctoral Program of Higher Education of China (No. 20092304120014), and the Foundation of Harbin Engineering University (Grant No. HEUFT09013)

References

Cheng G and Pan SX (2008) Nonlinear adaptive robust control of single-rod electro-hydraulic actuator with unknown nonlinear parameters. *IEEE Transactions on Control Systems Technology* 16(3): 434–445.

Claude K, Kenné JP, and Maarouf S (2006) Indirect adaptive control of an electro-hydraulic servo system based on nonlinear backstepping. In: *Proceedings of IEEE International Symposium on Industrial Electronics*, Montreal, QC, Canada, July 9–13, pp. 3147–3153.

Gregory LP (2003) Adaptive inverse control of linear and nonlinear systems using dynamic neural networks. *IEEE Transactions on Neural Networks* 14(2): 160–162.

Knohland T and Unbehaue NH (2000) Adaptive position control of electrohydraulic servo systems using ANN. *Mechatronic* 10: 127–143.

Lee JM, Kim HM, Park SH, and Kim JS (2009). A position control of electro-hydraulic actuator systems using the adaptive control scheme. In: *Proceedings of 2009 7th Asian Control Conference,* Hong Kong, People's Republic of China, August 27–29, pp. 21–26.

Li HR (1990) *Hydraulic Control System*. Beijing: National Defense Industry Press.

Liu ST and Han CZ (2000) *Adaptive Inverse Control*. Xi′an: Xi′an JiaoTong University.

Merritt HE (1967) *Hydraulic Control Systems*. New York: Wiley.

Plett GL (2002) Adaptive inverse control of unmodeled stable SISO and MIMO linear systems. *International Journal of Adaptive Control and Signal Processing* 16(4): 243–272.

Shafiq M and Shafiq MA (2009) Direct adaptive inverse control. *IEICE Electronics Express* 6(5): 223–225.

Simon H (2002) *Adaptive Filtering Theory*. Beijing: Publishing House of Electronics Industry.

Tagawa Y and Kajiwara K (2007) Controller development for the E-Defense shaking table. In: *Proceedings of the Institution of Mechanical Engineers Part 1, Journal of Systems and Control Engineering* 221(12): 171–181.

Wan, Y, Wu CW, and Zhang YG (2008) Electro-hydraulic proportional self-adaptive controller based on LSVM intelligent algorithm. In: *Proceedings of the 4th International Conference on Natural Computation*, Jinan, People's Republic of China, October 18–20, pp. 175–179.

Widrow B and Sterns SD (1985) *Adaptive Signal Processing*. New Jersey: Prentice-Hall.

Wu ZS, Fu BQ, Feng YB and Lai HJ (2005) Adaptive inverse controller and its application in electro-hydraulic servo system. *Journal of Harbin Institute of Technology* 37(3): 385–387.

Xu LN (1999) *Neural Network Control*. Harbin: Harbin Institute of Technology.

Yao JJ (2007) Research on acceleration harmonic cancellation of electro-hydraulic servo shaking table. PhD thesis, Harbin Institute of Technology, Harbin, People's Republic of China.

Yao JJ, Wang XC, Wu ZS and Han JW (2006) Variable structure control applied in electro-hydraulic servo system with ANN. *Chinese Journal of Mechanical Engineering* 19(1): 32–36.

Yao JJ, Wang LQ, Jiang HZ, Wu ZS and Han JW (2008a) Adaptive feed-forward compensator for harmonic cancellation in an electro-hydraulic servo system. *Chinese Journal of Mechanical Engineering* 21(1): 77–81.

Yao JJ, Wang LQ, Wang CD, Zhang ZL, and Jia P (2008b) ANN-based PID controller for an electro-hydraulic servo system. In: *Proceedings of the IEEE International Conference on Automation and Logistics*, Qingdao, People's Republic of China, September 1–3, pp. 18–22.

Yuan XF, Wang YN and Wu LH (2008) Adaptive inverse control of excitation system with actuator uncertainty. *Neural Processing Letters* 27(2): 125–136.

Zhang JT, Cheng DF, Liu YF, and Zhu GQ (2008) Adaptive fuzzy sliding mode control for missile electro-hydraulic servo mechanism. In: *Proceedings of the World Congress on Intelligent Control and Automation,* Chongqing, People's Republic of China, June 25–27, pp. 5197–5202.