Mechatronics and Automation Technology
J.-Y. Xu (Ed.)

doi:10.3233/ATDE231100

Experimental Study of Active Vibration Control for Flexible Truss by Using a Stewart Platform Manipulator

Bo LUO[1] , He YU, Fei FENG, Benzheng GAO and Yue GE
Academy of Launch Vehicle Technology, Beijing, 100076, China

Abstract. Experiments of active vibration control for flexible truss are studied, with a Stewart platform manipulator (SPM) employed as an active device at the bottom of the truss. A back-propagation neural network is designed to identity the controlled object. And on the basis of the identification model, this work constructs a neural network adaptive inverse controller (NNAIC). Then based on the dSPACE real-time simulation system, the control test system for the truss is built, on which the neural network adaptive inverse control experiments are carried out. The vibration amplitude decreases more than 93.8% and 89.6% with the structure continuously being excited at the first-order and second-order resonant frequency respectively. The results indicate the effectiveness of the control conducted by using SPM, and NNAIC has a good performance.

Keywords. Flexible space truss; Vibration control; NNAIC; Model identification.

1. Introduction

Vibration control for large flexible space truss structure is a challenging work in the field of aerospace dynamics and control. Large flexible space structure is being widely used in astronautic purpose since it has a lot of advantages as lightweight, reliable, simple and adaptable for tasks etc[1].

Large flexible space truss structure is easy to be excited low-frequency, nonlinear and huge amplitude vibrations, because of its large flexibility and low damping. However, it is difficult to attenuate when vibrations inevitably aroused by external and internal disturbances in space. Furthermore, the vibrations are highly coupled with the attitude motion of the spacecraft, bringing serious impact on normal operation of spacecraft payloads. Therefore, it is necessary to carry out active vibration control to solve this problem.

Large flexible space truss is normally designed to be extensible, which is folded in launch phase and deploy in space, such as the expandable arms of solar wings, and the stretchable structures of large antennas. If the active components are mounted in the truss to suppress the vibrations, it wound have an affect on the normal deployment [2]. Hence, to place active components at the connection between spacecraft body and flexible truss is an effective means. Kim[3] proposed the idea of “source-based vibration control”, settling a Stewart platform at the bottom of a slender structure to suppress vibrations. Hanieh[4] mounted a Stewart platform at the bottom of a truss, and used integral force feedback (IFF) controller to suppress the vibration of the truss.

[1] Corresponding Author, Bo LUO, Ph.D., Academy of Launch Vehicle Technology, 1 Nandahongmen Road, Beijing, 100076, China; E-mail: luobobuaa@163.com.

Li[5,6] used a Hexapod Active Manipulator to control the vibration of a two-link Flexible Joint Manipulator, and large flexible truss.

In researches of large flexible structure vibration control, different control methods were studied in literatures [7-11], whereas these methods are based on linear model. Although these methods avoid the nonlinear problem and bring convenience to the analysis and design of controller, they are not appropriate to the control problem of spacecraft with large angular and rapid maneuvering. Therefore, it is very meaningful to carry out the practical researches of active vibration control strategy suitable for nonlinear space structures. Neural network has proved successful in identification and control of dynamic systems [12-14].

Experiments of active vibration control for large flexible truss are researched in this paper, with a SPM employed as an active device on the bottom of the truss. The system composed of the rigid SPM and flexible truss is strong nonlinear and difficult to establish the accurate model, which is a rigid-flexible coupling dynamic system. A back-propagation neural network is designed to identity the controlled object. And on the basis of the identified model, this work constructs a neural network adaptive inverse controller (NNAIC). Then based on the dSPACE real-time simulation system, the control system for the truss is built, on which the neural work adaptive inverse control experiment is carried out. Results indicate the vibration amplitude decreases more than 93.8% and 89.6% with the structure continuously being excited at the first-order and second-order resonant frequency respectively.

2. “Source-based Vibration Control” Strategy

At present, the researches on vibration control for space flexible structures mainly focus on intelligence truss structures, in which active components integrated. However, this will definitely affect the normal stretching of the stretchable structures after launched in orbit. This paper adopts a "source-based vibration control" strategy, using an active SPM at the bottom of the flexible truss as its active control device, as shown in figure 1.

The SPM connects with the truss through three nodes A_1, A_2 and A_3 at the bottom of truss, as shown in figure 2. The SPM is a six dof parallel kinematic and dynamic mechanism with advantages of big stiffness, high stability, strong bearing capacity, small moving inertia and good dynamic performance. Therefore the SPM has wide application prospects in aspects of vibration isolation and target tracking[15].

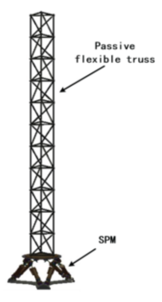

Figure 1. Passive truss mounted on the active SPM

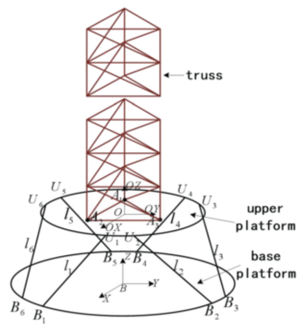

Figure 2. Schematic of SPM-truss system

3. Dynamics Identification of SPM-truss System by BP Neutral Network Adaptive Identifier

3.1. The Structure and Principle of BP Neural Network

The BP neural network (BPNN) is a multilayer forward network with good performance, suitable for approximation of multivariable nonlinear function. The typical BP network generally includes input layer, hidden and output layer, as figure 3 shows. In order to ensure the output of whole network able to take any value, the output layer of BPNN chooses pure linear function, and the output of BPNN equals the weighted sum of outputs of hidden layer.

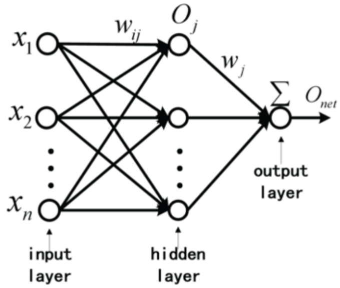

Figure 3. Structure of BP neutral network

Here x_i is input, w_{ij} is the weight of input layer, w_j is the weight of hidden layer, O_j is output of hidden layer. The output of whole network can be written as formula (1). In this paper, the hidden layer chooses sigmoid function, so the output of the hidden layer can be expressed as formula (2).

$$O_{net} = \sum_j w_j O_j \tag{1}$$

$$O_j = 1/(1+\exp(-\sum_i w_{ij} x_i)) \tag{2}$$

The BPNN has two kinds of learning parameters that are w_{ij} and w_j. And the update of them is often adopted the BP algorithm proposed by Rumelhart, the correction of network weights along the fastest negative gradient.

The learning process of BPNN is composed of two components that are positive propagation and back propagation. In process of positive propagation, input signals are disposed layer by layer from the input to output layer and the states of the neurons in each layer only affect the states of neurons in next layer. If the output cannot achieve the expect value, the back propagation would modify the weights of each layer by using the error signal, to minimum the error signal.

3.2. BP Neutral Network Adaptive Identifier

This paper adopts a SPM to connect with the bottom of the flexible truss, composing a rigid-flexible coupling system which shows strong nonlinear if the posture angles increase to large values. And the dynamic characteristic of each actuator of SPM is unknown, so the dynamic model of SPM-truss system is difficult to precisely build. However, the dynamic behaviors are implied in the inputs and outputs of the object, so we can get the dynamic model by system identification based on experiment.

The traditional identification methods usually use the linear ARX model as formula (3).

$$y_k = (a_1 y_{k-1} + a_2 y_{k-2} + \cdots + a_n y_{k-n}) + (b_0 u_k + b_1 u_{k-1} + \cdots + b_m u_{k-m}) \tag{3}$$

Here $u=\{u_k, u_{k-1}, u_{k-2}, \cdots, u_{k-m}\}$,$y=\{y_k, y_{k-1}, y_{k-2}, \cdots, y_{k-m}\}$ are the input and the output at now and past several moments. By using the least-square method, we can get an identification model for formula (3). For the linear systems, this identification method is very effective. However, if the object is of strong nonlinear, a big deviation will exist between the actual model and the model identified by least-square method. The dynamic model of a nonlinear system can be expressed as

$$y_k = g(y_{k-1}, y_{k-2}, \cdots y_{k-n}, u_k, u_{k-1}, \cdots, u_{k-m}) \tag{4}$$

Here g is a nonlinear function. Neutral network identification has an excellent performance since the neutral network has the ability of approaching arbitrary nonlinear function.

In order to obtain the dynamic model of SPM-truss system, the object researched in this paper, a BPNN adaptive identifier is designed, as shown in figure 4.

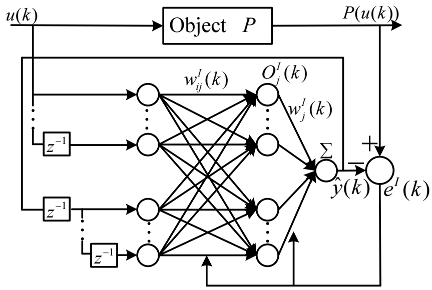

Figure 4. BPNN adaptive identifier

In figure 4, *u(k)*, *P(u(k))*, and $\hat{y}(k)$ are the input, output of actual object and output of BPNN respectively. The inputs of BPNN include *u(k)*, $\hat{y}(k)$ and their several delays. BPNN adaptive identifier uses the error $e^I(k)$ between *P(u(k))* and $\hat{y}(k)$ to adjust the weights of BPNN. It can serve as an online identifier as well as an offline identifier, just using the current input and output data. As in [16], the weights adjusting law can be formula (5).

$$\begin{cases} w^I_{ij}(k) = w^I_{ij}(k-1) + \eta^I e^I(k) O^I_j(k)(1 - O^I_j(k)) w_j(k) x^I_i(k) \\ w^I_j(k) = w^I_j(k-1) + \eta^I e^I(k) O^I_j(k) \end{cases} \tag{5}$$

$$[x^I_1, x^I_2, \cdots, x^I_n] = [u(k), u(k-1), \cdots, \hat{y}(k-1), \hat{y}(k-2), \cdots] \tag{6}$$

4. Neutral Network Adaptive Inverse Control

Adaptive Inverse Control (AIC)[17] is a very novel method in the field of control system design. The basic idea is to use a signal from a controller to drive the controlled object, and the transfer function of the controller is the inverse transfer function of the controlled object[18]. AIC has the advantages of simple structure, high stability, strong adaptive ability [19], of which mostly used is the X-filtering adaptive inverse control.

In order to make it suitable for the nonlinear system, this paper design a neural network adaptive inverse controller (NNAIC) based on neural network identification.

The NNAIC is mainly composed of the offline identification for the controlled system and the online adaptive inverse modeling, as figure 5 shows. Firstly, the referential signal *r* is submitted to a neutral network controller (NNC), of which the internal structure is also a BP neural network as figure 3 shows. The output signal u_c is used as the input signal of the controlled object *P2.* Then, NNC utilizes the total error *e*, which is the sum of the outputs of the disturbance channel *P1* and the control object channel *P2*, and the gradient information $\partial y/\partial u$ of *P2* to online adaptively adjust the weights of the controller, making the total error always tend to the minimum. The gradient information $\partial y/\partial u$ can be obtained by the offline identification model.

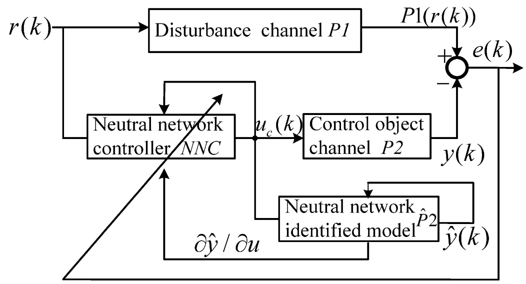

Figure 5. Schematic of NNAIC

The total error *e* can be expressed as

$$e(k) = P1(r(k)) - y(k) \tag{7}$$

$$y(k) = P2(u_c(k)) \tag{8}$$

Control target function is chosen

$$E(k) = \frac{1}{2}e^2(k) = \frac{1}{2}[P1(r(k)) - P2(u_c(k))]^2 \tag{9}$$

The output of NNC is

$$u(k) = \sum_j w_j(k)O_j(k) \tag{10}$$

From formula (2)

$$O_j(k) = 1/(1+\exp(-\sum_i w_{ij}(k)x_i(k))) \tag{11}$$

$$[x_1, x_2, \cdots, x_n] = [r(k), r(k-1), \cdots, u_c(k-1), u_c(k-2), \cdots] \tag{12}$$

The adjustment of weights is adopted BP algorithm and it can be calculated by using formula (13).

$$\Delta w_{ij}(k) = -\eta\frac{\partial E(k)}{\partial w_{ij}(k)} = \eta e\frac{\partial P2(k)}{\partial u(k)}O_j(k)(1-O_j(k))w_j(k)x_i(k) \tag{13}$$

$$\Delta w_j(k) = -\eta\frac{\partial E(k)}{\partial w_j(k)} = \eta e\frac{\partial P2(k)}{\partial u(k)}O_j(k) \tag{14}$$

This algorithm does not take account of the accumulated experience, only considering the current gradient information, and the learning process often oscillates. So adding a momentum to weights adjustment process, the weights adjusting law becomes formula (15). Here α is a constant.

$$\begin{cases} w_{ij}(k) = w_{ij}(k-1) + \Delta w_{ij} + \alpha(w_{ij}(k-1) - w_{ij}(k-2)) \\ w_j(k) = w_j(k-1) + \Delta w_j + \alpha(w_j(k-1) - w_j(k-2)) \end{cases} \tag{15}$$

In the above weights adjusting algorithm, the gradient information $\partial P2(k)/\partial u(k)$ of the control object is needed. Here use offline neural network identification model $\hat{P}2$ instead of *P2*. Here w_j^I, O_j^I and w_{1j}^I is respectively the weight of hidden layer, the output of hidden layer and the weight of input layer corresponds to the first input $u(k)$ in the identification model $\hat{P}2$.

$$\frac{\partial P2}{\partial u(k)} \approx \frac{\partial \hat{P}2}{\partial u(k)} = \sum_j w_j^I(k) O_j^I(k)(1 - O_j^I(k)) w_{1j}^I u(k) \tag{16}$$

5. Experiments Study

5.1. Description of Experimental System

The vibration control experiment system is mainly composed of the flexible truss, the SPM, Stewart control box, Elmo controller, accelerometer, exciter, charge amplifier and dSPACE, as figure 6 shows.

The flexible truss is a tri-prism truss of 17 bays with 3 nodes in each layer. Each node has a mass of 0.04kg besides the top three nodes placed with 3 additional large mass of 2kg. The horizontal and vertical rods in each bay are 168mm long, with cross-sectional diameter of 3mm. In order to reduce the natural frequency of truss, a diagonal rod is removed in each bay, as shown in figure 7. The truss has a characteristic of low and dense frequencies. The first two order frequencies are f_1=0.91Hz and f_2=3.48Hz of which the modal shapes are as shown in figure 8(a) and figure 8(b). Two accelerometers are mounted at the top two nodes of the truss, from which the signals entry the control system after they are amplified by charge amplifiers.

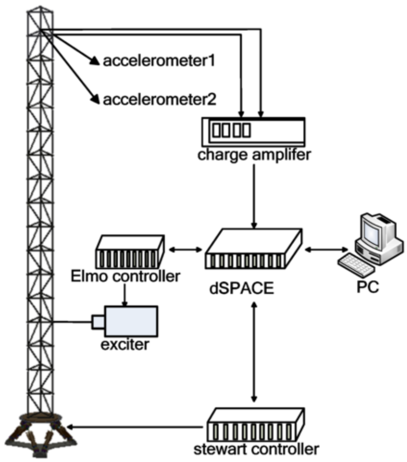

Figure 6. Experimental system

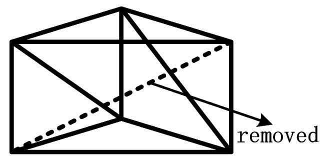

Figure 7. One bay on the truss

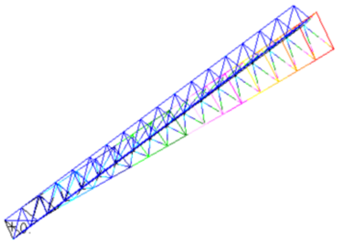

Figure 8(a). First-order modal of truss

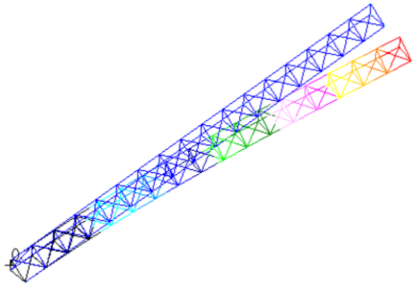

Figure 8(b). Second-order modal of truss

In this work, as shown in figure 9, the SPM are designed with rotation angular ranges of the upper platform relative to the base platform is -10.3°~9.8° along axis X, -10.0°~10.3° along axis Y, -11.6°~12.1° along axis Z. The translation ranges of the upper platform are -36.8~39.0*mm* along axis X, -33.6 ~33.8*mm* along axis Y, -38.4~35.3*mm* along axis Z.

Figure 9. Stewart platform manipulator

The exciter developed by author's laboratory is a linear motor actuator, with stroke grater than ±25*mm*, load capacity greater than 200N and rapid response.

5.2. Dynamic Offline Identification Results

The dynamic model of the control object is needed in NNAIC, so before the vibration control experiments, experiments for dynamic identification are accomplished. The 1st-order and 2nd-order modes of truss are torsion and bending respectively. To identify the dynamic performance of the object, this work uses the corresponding signals of SPM as the input signals of the BPNN adaptive identifier, and the measuring signals of accelerometer 1 and 2 after two integrals as the output signals of BPNN adaptive identifier respectively.

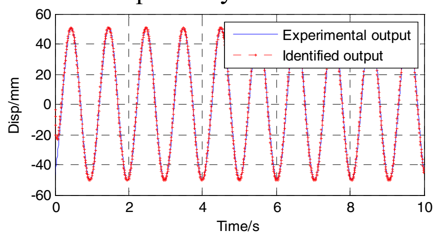

Figure 10. Indentified output with the 1st-order modal frequency

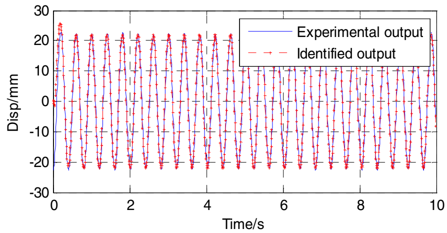

Figure 11. Indentified output with the 2nd-order modal frequency

The topological structure of the identifier is a BP neutral network of three layers, with 10 nodes of input layer and 10 nodes of hidden layer. Adopting a sinusoidal input as $u(k)=0.4sin(0.91*2\pi*h*k)$ (h=0.001 is the sampling step size), the output of the identification model and the experimental output are as shown in figure 10 for the 1st-order mode. Adopting another sinusoidal input as *u(k)=0.5sin(3.48*2π*h*k)*, the output of the identification model and the experimental output are as shown in figure 11 for the 2nd-order mode. Except in the initial short time, two signals are almost overlapped, which demonstrates the great performance of the BPNN adaptive identifier.

5.3. Vibration Control Experiment Results

This paper mainly adopted the neural network adaptive inverse controller (NNAIC) to suppress the vibrations of the first two modes of the truss excited by an exciter. Before the NNAIC works, the nature mode is aroused by the persistent sine disturbances generated by the exciter which connected with a node of the truss through a rigid pole. The topological structure of NNC is also a BP neutral network of three layers, with 10 nodes of input layer and 10 nodes of hidden layer. The sampling frequency of NNAIC is 1kHz. In the experiments, the controller starts work at 10th second after the truss was excited. Figure 12 shows the result of the 1st-order resonance control experiment. The amplitude at the node where accelerometer 1 installed is 50mm without control, and then declines 93.8% to less than 3.1mm with control. Figure 13 shows the result of the 2nd-order resonance control experiment. The amplitude at the node where accelerometer 2 installed is 22mm without control, and then declines 89.6% to less than 2.3mm with control. Figure 14 shows the length change of each actuator of SPM in the 1st-order resonance control experiment. Figure 15 shows the length change of each actuator of SPM in the 2nd-order resonance control experiment.

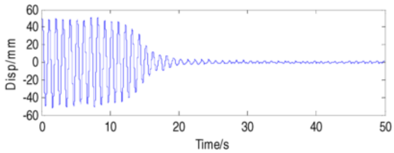

Figure 12. 1st-order resonance experiment using NNAIC

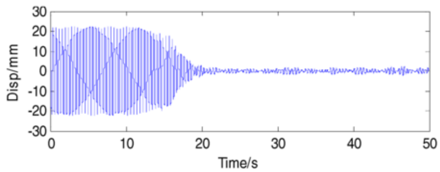

Figure 13. 2nd-order resonance experiment using NNAIC

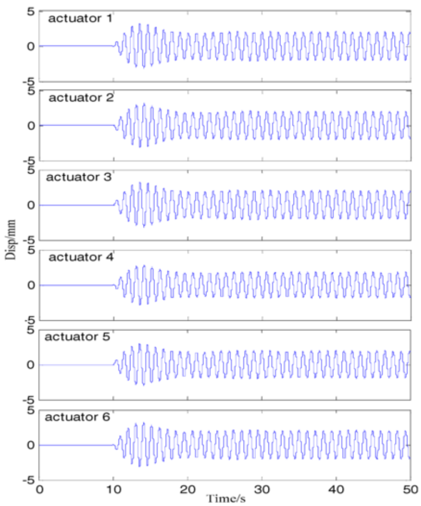

Figure 14. Length change of each actuator of SPM in the 1st-order resonance experiment

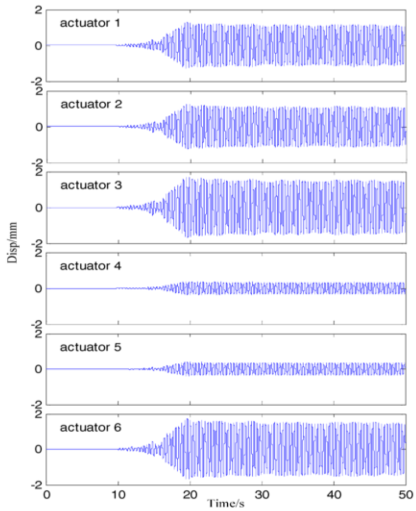

Figure 15. Length change of each actuator of SPM in the 2nd-order resonance experiment

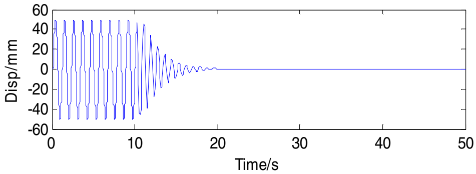

Figure 16. 1st-order resonance simulation using NNAIC

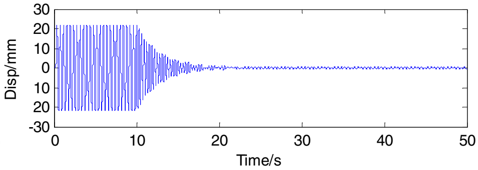

Figure 17. 2nd-order resonance simulation using NNAIC

Figure 16 and figure 17 show the simulation results of the 1st-order and 2nd-order resonance control simulation using the identification model respectively. There is a certain deviation between the results of simulation and experiment, due to the deviation between the offline identification model and the actual object, the error of experimental equipment, as well as inevitable environment noise etc. In conclusion, the neural network adaptive inverse controller designed in this paper is very effective to the vibration control for the large flexible truss structure.

6. Conclusions

- Through experiments, it is shown that the vibration of the large flexible truss can be effectively controlled by using Stewart platform manipulator (SPM) and the "source-based vibration control" strategy is practicable.
- A neutral network adaptive inverse controller is designed and applied to suppress the persistent vibrations of the truss aroused by an exciter. The vibration amplitude decreases more than 93.8% and 89.6% with the structure continuously being excited at the 1st-order and 2nd-order resonant frequency respectively.

References

[1] Si H W, Li D X, Chen W D. Dynamic and active control of large flexible space truss: A review[J]. Advances in Mechanics, 2008, 28(2): 167-176.

[2] A. Preumont, J. P. Dufour, C. Malekian, Active damping by a local force feedback with piezoelectric actuators[J]. AIAA J. of Guidance, 1992, 15(2):390-395.

[3] Nag-In Kim, Chong-won Lee. Multi-axis vibration control of a slender structure by using Stewart plantform manipulator[J]. Mechanism and Machine Theory, 36(2001):1253-1269.

[4] Kristin D. Culler Active isolation and pointing using flextensional piezoelectric actuators[J]. AIAA Journal, 2001(39).

[5] W.P. Li, B. Luo, H. Huang. Active Vibration Control of Flexible Joint Manipulator using Input Shaping and Adaptive Parameter Auto Disturbance Rejection Controller[J]. Journal of Sound and Vibration, 2016, (363): 97-125.

[6] Li W P, Yuan S N, Hai Huang. Adaptive Fuzzy Vibration Control of Large Flexible Truss with Hexapod Active Interface[C]. International Conference on Systems and Informatics, 2012, 351-365.

[7] Zhao G W, Huang H X, Ren W. Flexible adaptive truss testbed and its optimal control experiment for vibration[J]. Journal of Beijing University of Aeronautics and Astronautics, 2005, 31(14):434-437.

[8] Wei Y D, Chen DZ, Chen Y D. Mode control of vibration in piezoelectric cantilever beam[J]. Journal of Zhejiang University, 2004, 38(9):1180-1184.

[9] Wu D F, Liu A C, et al. Study on active vibration control of piezoelectric intelligent flexible beam[J]. Journal of Beijing University of Aeronautics and Astronautics, 2004, 30(2):160-163.

[10] Bruno de Marneffe. Active and Passive Vibration Isolation and Damping via Shunted Transducer[D]. PhD thesis, UNIVERSITE LIBER DE BRUXELLES, 2007.
[11] Liu S K, Yan G R. Active Vibration Control for the Space Truss Structure Based on Adaptive Inverse Control[C]. The 9th National Conference of Vibration Theory and Application of Academic, 2007.
[12] Gao H J, Song Y H, et al. Modeling and neural network control of a flexible beam with unknown spatiotemporally varying disturbance using assumed mode method[J]. Neurocomputing. 2018(314):458-467.
[13] B. S. Kim, A. J. Calise, Nonlinear flight control using neural networks[J]. AIAA Journal of Guidance Control and Dynamics, 1997, 20(1):26-33.
[14] M. M. Korjani, O. Bazzaz, M. B. Menhaj. Real time identification and control of dynamic systems using recurrent neural networks[J]. Artificial Intelligence Review, 2008, (30):1-17.
[15] Li W P. Pointing and vibration control of space-base high stability precise pointing and traking Hexapod[D]. PhD thesis, Beijing University of Aeronautics and Astronautics, China, 2008.
[16] Pang Z H, Cui H. System identification and adaptive control: MATLAB simulation[M]. Beihang University Press, 2009.
[17] B.Widrow, E.Walach. Adaptive inverse control[M]. Interpret by Liu Shutang, Han Chongzhao. Xi'an Jiaotong University Press. 2000:1-147.
[18] Cui L. Large-stroke hexapod platform design and control[D]. PhD thesis, Beijing university of Aeronautics and Astronautics, China, 2009.
[19] Cui L, Huang H. Large-stroke hexapod platform and its vibration isolation test[J]. Journal of Beijing University of Aeronautics and Astronautics 2010; 36(6): 671-675.