Available online at www.sciencedirect.com
SCIENCE DIRECT
ELSEVIER
Journal of Sound and Vibration 272 (2004) 437–449
JOURNAL OF SOUND AND VIBRATION
www.elsevier.com/locate/jsvi

Letter to the Editor

Active noise control using a simplified fuzzy neural network

Qi-Zhi Zhang[a,*], Woon-Seng Gan[b]

[a] *Department of Computer Science and Automation, Beijing Institute of Machinery, P.O. Box 2865, Beijing 100085, People's Republic of China*

[b] *School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798, Singapore*

Received 7 April 2003; accepted 26 June 2003

1. Introduction

Active noise control (ANC) based on the principle of superposition has become an important and interesting topic of much research in recent years. In ANC system, a secondary source is introduced to generate anti-noise of equal amplitude and opposite phase with the primary noise. The acoustical and electrical control basis of ANC system is introduced in Ref. [1]. According to the acoustic principle, active attenuation is a more attractive mean to achieve larger amount of noise reduction in a small zone or in a duct, particularly at low frequencies. Various adaptive algorithms are developed, and many commercial applications of ANC system are introduced in Ref. [2]. A popular adaptive filtering algorithm is the filter-x least mean square (FXLMS) algorithm for finite impulse response (FIR) filter [1,2], because it is simple and has relatively low computational load. The development of improved digital signal processing (DSP) hardware allows more sophisticated algorithms to be implemented in real time to improve the system performance [3]. To design a practical ANC system, two important problems should be considered. Firstly, the secondary path may be time variable. If the phase difference for a particular frequency between the actual and the estimated model is more than 90°, the ANC system can become unstable [2]. Secondly, the secondary path and primary path may exhibit non-linear behaviors. Various techniques can be utilized to solve the first problem. Online modelling control techniques [2,4,5], robust control technique [6], and without modeling control technique [7] have been introduced to design the ANC system with time-varying secondary path. Neural network (NN) has been introduced to control non-linear noise, and multilayer perceptron neural networks were used to control non-linear plants [8]. The multilayer perceptron neural network is a global approximate neural network, and the major problem in the NN-based ANC is its relatively slow learning (or convergence) process. To solve the problem mentioned above, several strategies can be adopted. One is the fast NN learning algorithm utilized in the control system [9], and the other is the NN enhanced controller used in the ANC system [10]. In addition, the local

*Corresponding author. Tel.: +86010-62939173.
E-mail address: zhang_qz@sohu.com (Q.-Z. Zhang).

doi:10.1016/S0022-460X(03)00742-9

approximate neural network, radial basis function (RBF) networks [11], can be introduced to improve the performance of the convergence. Recently, the fuzzy neural networks [12] and fuzzy modeling technique [13] are used as a non-linear filter. In [13], both acoustic model of the primary path and inverse model of the secondary path are identified using the Takagi-Sugeno (TS) model, and the experimental results have been obtained for a multi-channel ANC system. Since an open-loop strategy is utilized in the ANC system, the performance of the ANC system will be degraded by disturbances and model mismatches. The NN and RBF networks can be trained by numerical data only, but the fuzzy neural network can handle both numerical information and linguistic information. Since the fuzzy neural network is a local approximate model, the adaptive process can be accelerated. This paper will focus on the active noise control problem for non-linear response of an unknown primary acoustic path. The primary path exhibits non-linear distortion when the primary noise propagating in a duct has high sound pressure [14]. A feedforward fuzzy neural network controller is proposed, where the model of fuzzy neural network is simplified to meet the characteristic of an ANC system. The stability of the closed loop system is proven via the discrete Lyapunov function. Some digital simulations with non-linear primary noise path are given, and the results show that the simplified fuzzy neural controller is more effective compared to the classical NN controller.

2. System description

An ANC system with non-linear primary noise path is shown in Fig. 1. The secondary path is modeled with a FIR filter. The ANC system can be described by the following equation:

$$e(k+1) = d(k+1) + y(k+1) = g(X(k)) + \sum_{j=0}^{m} h(j)u(k-j), \tag{1}$$

where $X(k) = [x(k)x(k-1)\ldots x(k-n)]^{\mathrm{T}}$ is the reference signal vector, $u(k)$ is the output of non-linear controller, and $h(j)(j = 0, 1\ldots m)$ is the FIR filter coefficients of the secondary path model. d is the disturbance signal received at the error microphone, and $g(.)$ is a smoothing non-linear function. The output of the feedforward non-linear controller can be expressed as

$$u(k) = f(X(k), W), \tag{2}$$

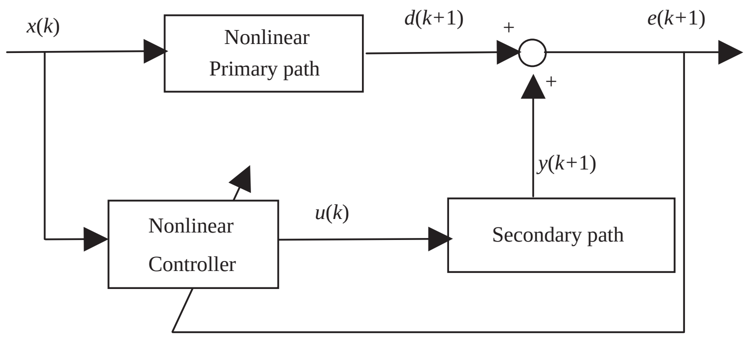

Fig. 1. Block diagram of a non-linear control system.

where $f(.)$ is a smoothing non-linear function, and W is a parameter vector. The neural network is utilized as the non-linear controller, where W is the weights vector. The performance index can be described as

$$J(k+1) = \tfrac{1}{2}e^2(k+1) = \tfrac{1}{2}[y(k+1) + d(k+1)]^2. \tag{3}$$

The unknown parameters can be adjusted according to the gradient descent method

$$W(k+1) = W(k) - \mu\frac{\partial J(k+1)}{\partial W(k)} = W(k) - \mu e(k+1)\frac{\partial y(k+1)}{\partial W(k)}, \tag{4}$$

where μ is the learning rate. Applying the chain rule to Eq. (4):

$$\frac{\partial y(k+1)}{\partial W(k)} = \sum_{j=0}^{m}\frac{\partial y(k+1)}{\partial u(k-j)}\frac{\partial u(k-j)}{\partial W(k)} = \sum_{j=0}^{m} h(j)\frac{\partial u(k-j)}{\partial W(k)}.. \tag{5}$$

If the weights, $W(k)$ are made to adapt slowly enough with time, the gradients of u in Eq. (5) can be approximately written as

$$\frac{\partial u(k-j)}{\partial W(k)} \approx \frac{\partial u(k-j)}{\partial W(k-j)} = \left.\frac{\partial f(X,W)}{\partial W}\right|_{X=X(k-j),W=W(k-j)}. \tag{6}$$

The parameters of non-linear controller can be adjusted on-line using the update rule Eq. (4), with gradients calculated in Eqs. (5) and (6).

3. Structure of the fuzzy neural network

In Section 2, a general feedforward non-linear controller is proposed. Due to the universal approximation ability, the neural network can be selected to approximate the non-linear controller $f(X(k), W)$. The vector, W is the weights of the neural network. Several neural networks, such as, multi-layer perceptrons (MLP), radial basis function (RBF) networks, and fuzzy neural networks (FNN), etc can be selected. In this paper, the fuzzy neural network is used as a non-linear filter. It can handle both numerical information and linguistic information, and therefore, accelerates the adaptation process.

A fuzzy neural network structure is shown in Fig. 2. The system has five layers as proposed in Refs. [12,15,16]. A model with two inputs and a single output is considered here for convenience.

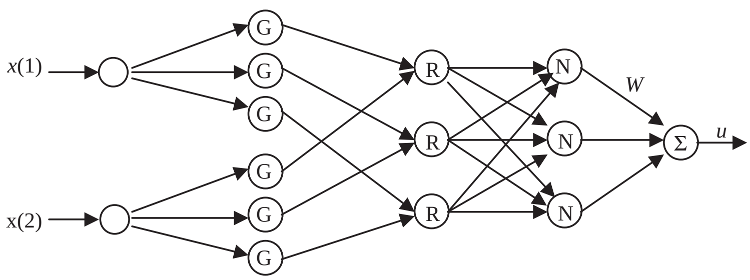

Fig. 2. Structure of five-layered fuzzy neural network.

Nodes in layer 1 are input nodes that directly transmit input signals to the next layer. Layer 5 is the output layer. Nodes in layer 2 are "term nodes, G" and they act as membership functions to express the input fuzzy linguistic variables. A Gaussian function is adopted to present the membership function, in which the mean value m and the variance σ can be adjusted through the learning process. The two fuzzy sets of the first and the second input variables consist of n_1 and n_2 linguistic terms, respectively. Each node in layer 3 is called a "rule node, R" and represents a single fuzzy rule. In total, there are $n_1 \times n_2$ nodes in layer 3 to form a fuzzy rule base for two linguistic input variables. Nodes in layer 4, N perform the normalization of firing strengths coming from layer 3, and the input links are fully connected. The number of nodes in this layer is equal to that of nodes in layer 3. In the following descriptions, the symbol $v_i^{(k)}$ denotes the ith input of node in the kth layer, and the symbol $a^{(k)}$ denotes the output of node in the kth layer. To give a clear understanding of the fuzzy neural network, the functions of the from layer 1 to layer 5 are defined as follows:

Layer 1: the nodes in this layer only transmit input values to the nodes of the next layer directly:

$$a^{(1)} = v_i^{(1)}. \tag{7}$$

Layer 2: the nodes in this layer represent Gaussian membership functions. The functions of the nodes are defined as follows:

$$a^{(2)} = \exp\left\{-\frac{(v_i^{(2)} - m_{ij})^2}{\sigma_{ij}^2}\right\}, \tag{8}$$

where m_{ij} and σ_{ij} are the center and the width of the Gaussian membership function of jth term of the ith input variable $x(i)$, respectively.

Layer 3: the nodes in this layer are rule nodes. The rule nodes perform a fuzzy AND operation (or product inference) to calculate the firing strength

$$a^{(3)} = \prod_i v_i^{(3)}. \tag{9}$$

Layer 4: Nodes in layer 4 perform the normalization of firing strengths coming from layer 3

$$a^{(4)} = \frac{v_i^{(4)}}{\sum_i v_i^{(4)}}. \tag{10}$$

Layer 5: This layer is the output layer. The link weights in this layer represent the singleton constituents (W_i) of the output variable. The output node integrates all the normalized firing strengths from layer 4 with the corresponding singleton constituents and act as a defuzzifier:

$$u = a^{(5)} = \sum_i v_i^{(5)} W_i. \tag{11}$$

In the next section, we shall discuss the learning algorithm of the fuzzy neural network and apply the fuzzy neural network to control the non-linear ANC system.

4. The adaptive control approach using a simplified fuzzy neural network

Generally, the learning algorithm of the fuzzy neural network consists of two major components:

(1) Input/output space partitioning and construction of fuzzy rules. Several clustering algorithms were developed to estimate the center and variance of each cluster for the construction of the initial structure of the fuzzy neural network [12,15,16]. The input/output space can be partitioned by a clustering algorithm or by a priori knowledge.
(2) *Parameters identification*. Parameters can be optimized by the simple gradient descent method [12] or by the complex recursive least squares and Levenberg–Marquardt algorithms to accelerate the learning convergence [16].

In this paper, the input space is partitioned by a priori knowledge. The gradient descent method is utilized to adjust the parameters of the fuzzy neural network. Fig. 3 gives the block diagram of a FNN-based ANC system. Compared to Fig. 1, the FNN controller is selected to replace the non-linear controller. The FNN controller is a non-linear tap-delay filter, and the input of the FNN is the reference $x(k)$ and its delays are $x(k-1), x(k-2), \ldots, x(k-n)$. We assume that the fuzzy set for every input variable consists of N linguistic terms. There are a total of $2(n+1)N$ parameters, with $(n+1)N$ centers and $(n+1)N$ widths of the Gaussian membership function in layer 2. Since the inputs have the same distributing function, we can set all the centers and widths of the Gaussian membership functions to the same value, for different input variables:

$$m_{ij} = m_{1j}, \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, N, \tag{12}$$

$$\sigma_{ij} = \sigma_{1j}, \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, N. \tag{13}$$

Therefore, only $2N$ parameters are required in layer 2, and the parameters in layer 2 should be greatly reduced when the input variables are large. The computational load can be reduced as follows. According to Eqs. (8), (12) and (13), if the outputs in layer 2 for the first input variable $x(k)$ have been calculated, then the outputs in layer 2 for other input variables, $x(k-i), i = 1, \ldots, n$, are only the delay of the outputs for the first input variable. Fig. 4 shows the structure of the simplified FNN (SFNN). The nodes labeled as D are delay nodes, whose outputs are the one

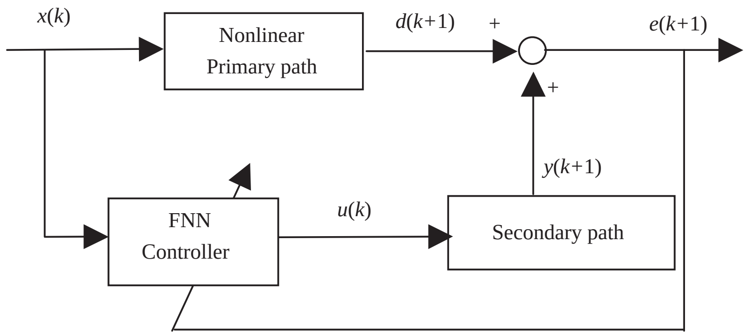

Fig. 3. Block diagram of an FNN-based ANC system.

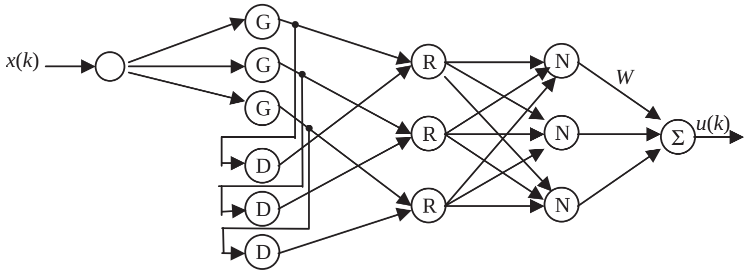

Fig. 4. Structure of the simplified fuzzy neural network.

period delay of the inputs. It can be found that only the current reference noise signal is used as the input to the SFNN.

It is presumed that the input space is partitioned by a priori knowledge. Only the singleton constituents (W_i) of the output variable are adaptively adjusted when the ANC system is running. The rule of adaptive learning is stated as

$$W(k+1) = W(k) - \mu e(k+1)\sum_{j=0}^{m} h(j) \cdot A(k-j), \tag{14}$$

where $A(k)$ is the vector which consists of the outputs of the layer 4.

5. The stability of control system

The discrete-type Lyapunov function can be given by

$$V(k) = \tfrac{1}{2}e^2(k). \tag{15}$$

Due to the training process, the change of the Lyapunov function can be obtained by

$$\Delta V(k) = V(k+1) - V(k) = \tfrac{1}{2}[e^2(k+1) - e^2(k)]. \tag{16}$$

The error difference resulting from the learning can be represented by

$$e(k+1) = e(k) + \Delta e(k) = e(k) + \left[\frac{\partial e(k)}{\partial W(k)}\right]^{\mathrm{T}} \Delta W(k). \tag{17}$$

According to the update rule of the weights, we can obtain

$$\Delta W(k) = -\mu e(k)\sum_{j=0}^{n} h(j)\frac{\partial u(k-j)}{\partial W(k)} = -\mu e(k) H\mathbf{A}(k), \tag{18}$$

where

$$H = [h(0)h(1)\ldots h(m)], \quad \mathbf{A}(k) = [A(k)A(k-1)\ldots A(k-m)]^{\mathrm{T}}. \tag{19}$$

A general stability theorem can be presented as follows:

Theorem. Let μ be the learning rate for the weights of the SFNN. We define $g_0 = \|H\|$, where $\|\bullet\|$ is the norm of matrix or vector. If the learning rate μ is chosen as $0<\mu<2/(g_0)^2$, then the local stability of closed loop control system based on neural network is guaranteed.

Proof. Define $\mathbf{Q}(k) = H\mathbf{A}(k)$, According to Eqs. (16)–(19), $\Delta V(k)$ can be represented as

$$\begin{aligned}\Delta V(k) &= \Delta e(k)[2e(k) + \Delta e(k)]/2 = -\frac{1}{2}\left[\frac{\partial e(k)}{\partial W(k)}\right]^{\mathrm{T}} \mu e(k) H\mathbf{A}(k) \\ &\times \left\{2e(k) - \left[\frac{\partial e(k)}{\partial W(k)}\right]^{\mathrm{T}} \mu e(k) H\mathbf{A}(k)\right\} = -\frac{1}{2}\mu e(k)\|\mathbf{Q}(k)\|^2 \\ &\times \{2e(k) - e(k)\|\mathbf{Q}(k)\|^2\} = -\frac{1}{2}\mu e^2(k)\|\mathbf{Q}(k)\|^2\{2 - \mu\|\mathbf{Q}(k)\|^2\} = -\frac{1}{2}\lambda e^2(k). \end{aligned} \tag{20}$$

Since $\|\mathbf{Q}(k)\| \leqslant \|H\|\,\|\mathbf{A}(k)\| \leqslant g_0$, if the learning rate μ is chosen as $0<\mu<2/(g_0)^2$, then $0<\mu<2/\|\mathbf{Q}(k)\|^2$, which implies that $\lambda = \mu\|\mathbf{Q}(k)\|^2\{2 - \mu\|\mathbf{Q}(k)\|^2\} > 0$ and $\Delta V(k)<0$. Therefore, the control system is locally stable. □

6. Simulation results

In this section, some illustrative results are presented to compare the performances of the two different systems: the neural networks (NN) control and the simplified fuzzy neural networks control (SFNN). The sampling frequency used in this simulation is 1000 Hz. The disturbance signal is chosen to be a 50 Hz pure tone signal plus an additional Gaussian white noise signal. The number of neurons in NN is 4–4–1. There is one input node and one output node in the SFNN. The input space is partitioned to 8 fuzzy sets, and the centers and widths of Gaussian membership functions are selected as

$$\begin{aligned}\mathbf{m} &= [-0.65,\ -5/8,\ -3/8,\ -1/8,\ 1/8,\ 3/8,\ 5/8,\ 0.65], \\ \boldsymbol{\sigma} &= [-20,\ 0.14,\ 0.14,\ 0.14,\ 0.14,\ 0.14,\ 0.14,\ 20].\end{aligned}$$

There are 4 input variables in layer 1, and they are realized by delaying the outputs of layer 2. Only the W vector is adjusted online, and the centers and widths of Gaussian membership functions remain fixed when the ANC system is running.

Case 1: An active noise control example with non-linear primary acoustic path is selected to illustrate the effectiveness of the SFNN by comparing with the results given by NN. The learning rate for W in the SFNN is chosen as $\mu = 1.8$, and the learning rate for the weights in the NN is chosen as $\mu = 0.04$. The acoustic paths are chosen as follows:

The primary acoustic path from noise source to error microphone is

$$\begin{aligned}d(k+1) = {} & 0.8x(k-2) + 0.6x(k-3) - 0.2x(k-4) - 0.5x(k-5) \\ & - 0.1x(k-6) + 0.4x(k-7) - 0.05x(k-8) + 0.9x^2(k-2).\end{aligned}$$

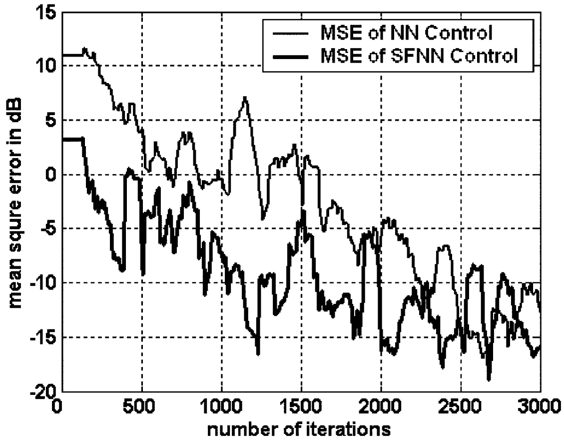

Fig. 5. Performance comparison, the thin line for NN controller, and the thick line for SFNN controller.

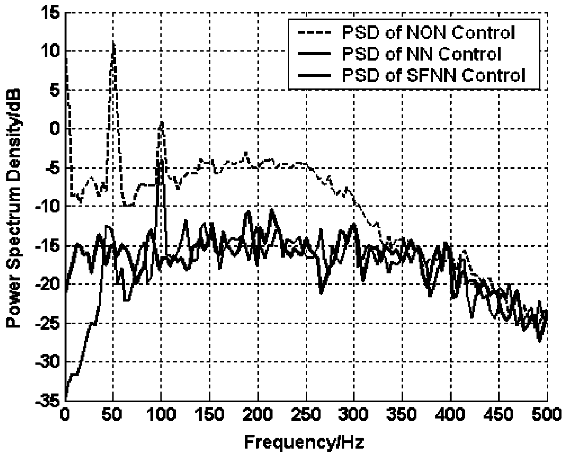

Fig. 6. Power spectrum of active noise canceling errors. The thin line for NN controller, the thick line for SFNN and the dished line for ANC turn off.

The secondary acoustic path from secondary source to error microphone is

$$y(k+1) = u(k-1) + 0.6u(k2) + 0.1u(k-3) - 0.1u(k-4) - 0.005u(k-5).$$

Fig. 5 shows the mean square error (MSE) in error microphone versus the number of iterations. The result of the NN-based ANC system is shown in the solid thin line, and the result of the SFNN-based ANC system is shown in solid thick line. The MSE of the SFNN control system is approximately 5 dB below that of the NN control system. The convergence rate of the SFNN is faster than that of the NN.

Fig. 6 gives the simulating results of the canceling errors between 2000 and 3000 iterations in the frequency domain. The result of the NN is shown in the solid thin line, the result of the SFNN is shown in solid thick line, and the dashed line shows the sound pressure level of the disturbance

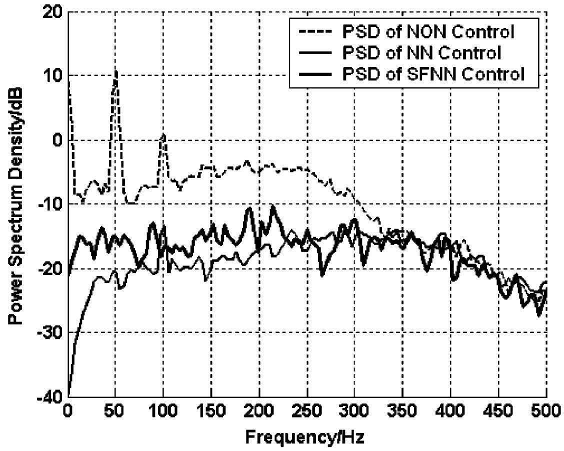

Fig. 7. Power spectrum of active noise canceling errors. The thin line for NN controller (after 8000 iterations), and the thick line for SFNN controller (after 2000 iterations), and the dished line for ANC turn off.

signal when the ANC system turns off. It can be seen that using both control methods (NN and SFNN), the 50 Hz tone can be reduced by about 25 dB, and broadband noise can be reduced by about 10 dB. In Fig. 6, there is a 100 Hz peak in the noise spectrum, which is produced by the square non-linear in the primary acoustic path. It can be reduced by 15 dB using the SFNN control, but it can only be reduced by 5 dB using the NN control. For non-linear control problem, the SFNN control is clearly superior to the NN control.

Fig. 7 gives another simulation results of the canceling errors in the frequency domain. The result of the NN control is calculated by the data between 8000 and 9000 iterations. Other results are similar to that shown in Fig. 6. From the results shown in Figs. 5–7, it can be seen that both methods (NN and SFNN), can reduce the broadband noise and the non-linear noise. But, to achieve the similar canceling error, the number of iterations in the NN control is three times the number of iterations in the SFNN control.

To show the advantage of proposed method, another two simulation examples are given. The primary acoustic paths are non-linear in both simulation examples. The secondary path with minimum phase is selected in one model, and the secondary path with non-minimum phase is selected in the other model [14].

Case 2: Simulations are given for the secondary path with minimum phase. The learning rate for W in the SFNN is chosen as $\mu = 1.0$, and the learning rate for the weights in the NN is chosen as $\mu = 0.08$. The acoustic paths are chosen as follows:

The primary acoustic path is selected as

$$d(k+1) = x(k-4) - 0.3x(k-5) + 0.2x(k-6) + 0.9x^2(k-4).$$

The secondary acoustic path from secondary source to error microphone is

$$y(k+1) = u(k-1) + 0.5u(k-2).$$

Figs. 8–10 show the simulating results of the NN control and the SFNN control. The performances in these figures are similar to that reported in case 1. From the results shown in

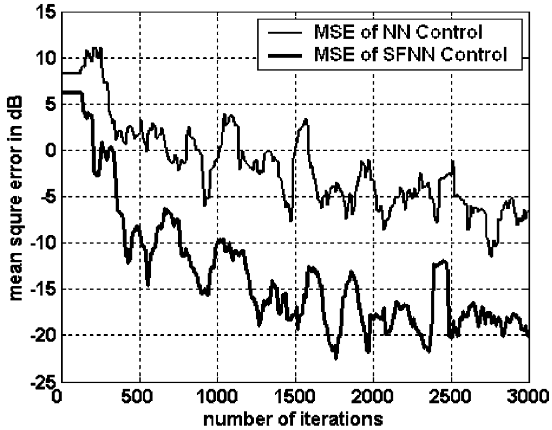

Fig. 8. Performance comparison, the thin line for NN controller, and the thick line for SFNN controller.

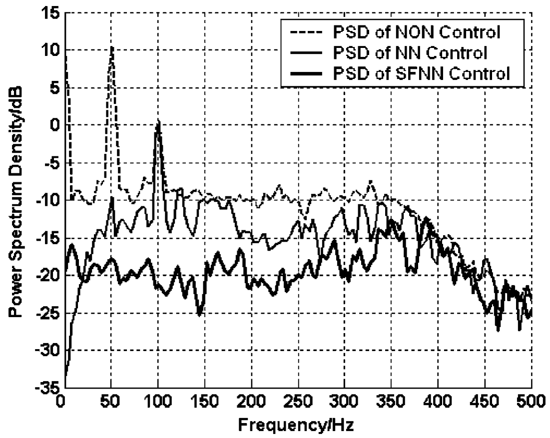

Fig. 9. Power spectrum of active noise canceling errors. The thin line for NN controller, the thick line for SFNN and the dished line for ANC turn off.

Figs. 8–10, it can be seen that the convergence of the SFNN control is superior to that of the NN control for the secondary path with minimum phase.

Case 3: simulations are given for the secondary path with non-minimum phase. The learning rate for W in the SFNN is chosen as $\mu = 1.0$, and the learning rate for the weights in the NN is chosen as $\mu = 0.06$. The acoustic paths are chosen as follows

The primary acoustic path is selected as

$$d(k+1) = x(k-4) - 0.3x(k-5) + 0.2x(k-6) + 0.9x^2(k-4).$$

The secondary acoustic path from secondary source to error microphone is

$$y(k+1) = u(k-1) + 1.5u(k-2) - u(k-3).$$

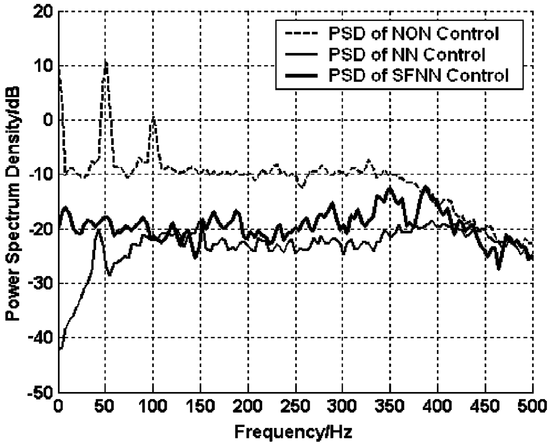

Fig. 10. Power spectrum of active noise canceling errors. The thin line for NN controller (after 8000 iterations), and the thick line for SFNN controller (after 2000 iterations), and the dished line for ANC turn off.

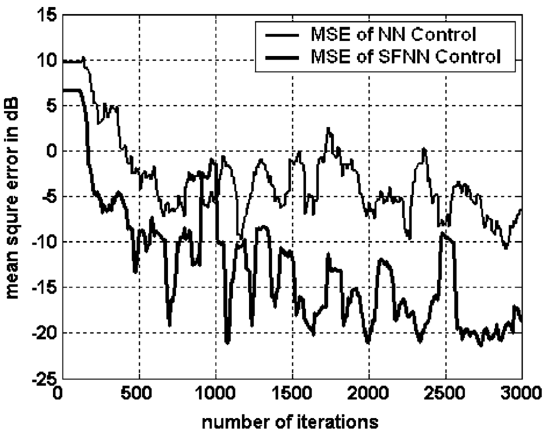

Fig. 11. Performance comparison, the thin line for NN controller, and the thick line for SFNN controller.

Figs. 11–13 show the simulating results of the NN control and the SFNN control. Comparing with case 2, it can be seen that the performances of the ANC system have been degraded by the secondary path with non-minimum phase. Contrast to the SFNN based ANC system, the performances of the NN based ANC system are obviously degraded. From the results shown in Figs. 11–13, it can be seen that the convergence of the SFNN control is superior to that of the NN control for secondary path with non-minimum phase.

7. Conclusions

The non-linear active noise control (ANC) is studied. A simplified fuzzy neural network (SFNN) is proposed to solve the non-linear effect in the primary acoustic path of the ANC

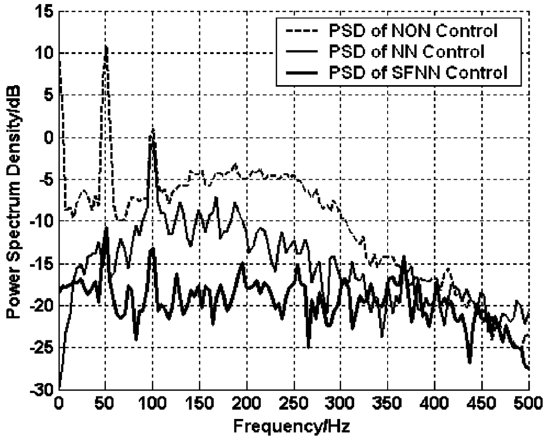

Fig. 12. Power spectrum of active noise canceling errors. The thin line for NN controller, the thick line for SFNN and the dished line for ANC turn off.

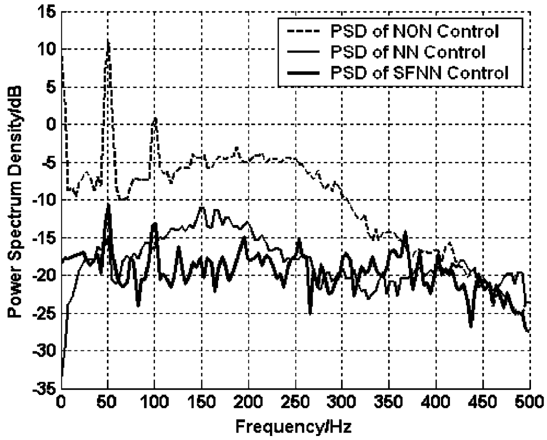

Fig. 13. Power spectrum of active noise canceling errors. The thin line for NN controller (after 8000 iterations), and the thick line for SFNN controller (after 2000 iterations), and the dished line for ANC turn off.

system. Using the SFNN, only one input is required, and fewer parameters are utilized. Since the SFNN is a local approximated neural network, the rate convergence of the SFNN is faster than that of the global approximated neural network. An on-line learning algorithm based on the error gradient descent method is proposed, and the local stability of closed loop system is proven via the discrete Lyapunov function. Some simulation results are given to compare the proposed control method with NN based method. The results show that the adaptive active noise control method based on the SFNN is very effective to the non-linear noise control, and the convergence of the SFNN control is superior to that of the NN control.

Our current work is focusing on designing an ANC system based on recurrent fuzzy neural network, considering online modelling techniques to meet the requirement and constraints of practical applications.

Acknowledgements

This research is supported by Science Funds of Educational Committee of Beijing City (KM200311232137) and Training Funds for Elitist of Beijing.

References

[1] S.J. Elliott, P.A. Nelson, Active noise control, *IEEE Signal Process Magazine* 10 (1993) 12–35.
[2] S.M. Kuo, D.R. Morgan, Active noise control: a tutorial review, *IEEE Proceedings* 87 (1999) 973–993.
[3] S.M. Kuo, W.S. Gan, *Digital Signal Processors: Architecture, Implementation, and Applications*, Prentice Hall, Englewood Cliffs, NJ, 2004.
[4] X.J. Qiu, C.H. Hansen, A modified filtered-*x* LMS Algorithm for active control of periodic noise with on-line cancellation path modeling, *Journal of Low Frequency Noise, Vibration and Active Control* 19 (2000) 35–46.
[5] M. Zhang, H. Lan, W. Ser, A robust online secondary path modeling method with auxiliary noise power scheduling strategy and norm constraint manipulation, *IEEE Transactions on Speech and Audio Processing* 11 (2003) 45–53.
[6] W.K. Tseng, B. Rafaely, S.J. Elliott, Performance limits and real-time implementation of a virtual microphone active headrest, *Active2002,* ISVR, Southampton, UK, 2002, pp. 1231–1242.
[7] Y. Maeda, T. Yoshida, An active noise control without estimation of secondary path–ANC using simultaneous perturbation, *Active1999*, Florida, USA, 1999, pp. 985–994.
[8] M. Bouchard, B. Pailard, C.T.L. Dinh, Improved training of neural networks for the nonlinear active control of sound and vibration, *IEEE Transactions on Neural Networks* 10 (1999) 391–401.
[9] M. Bouchard, New recursive-least-squares algorithms for non-linear active control of sound and vibrations using neural networks, *IEEE Transactions on Neural Networks* 12 (2001) 135–147.
[10] Q.Z. Zhang, Y.L. Jia, Active noise hybrid feedforward /feedback control using neural network compensation, *American Society of Mechanical Engineers, Journal of Vibration And Acoustics* 124 (2002) 100–104.
[11] P. Strauch, B. Mulgrew, Active control of nonlinear noise processes in a linear duct, *IEEE Transactions on Signal Processing* 46 (1998) 2404–2412.
[12] C.F. Juang, C.T. Lin, Noisy speech processing by recurrently adaptive fuzzy filters, *IEEE Transactions on Fuzzy Systems* 9 (2001) 139–152.
[13] J.M. Sousa, C.A. Silva, J.M.G. Costa, Fuzzy active noise modeling and control, *International Journal of Approximate Reasoning* 33 (2003) 51–70.
[14] L. Tan, J. Jiang, Adaptive volterra filters for active control of nonlinear noise processes, *IEEE Transactions on Signal Processing* 49 (2001) 1667–1676.
[15] W.A. Farag, V.H. Quintana, L.T. Germano, A genetic-based neuro-fuzzy approach for modeling and control of dynamical systems, *IEEE Transactions on Neural Networks* 9 (1998) 756–767.
[16] J.S. Wang, C.S. Lee, Self-adaptive neuro-fuzzy inference systems for classification applications, *IEEE Transactions on Fuzzy Systems,* 10 (2002) 790–802.