ADAPTIVE NEURAL NETWORK FOR FEEDBACK ACTIVE NOISE CONTROL SYSTEM

Huynh Van Tuan[(1)], Nguyen Huu Phuong[(1)], Nguyen Ngoc Long[(2)]
(1) University of Science, VNU-HCMC
(2) Ton Duc Thang University

ABSTRACT: *This paper presents a neural-based filtered-X least-mean-square algorithm (NFXLMS) active noise control (ANC) system. The saturation of the power amplifier in ANC system is considered. A method for compensating the saturation is proposed. On line dynamic learning algorithms based on the error gradient descent method is carried out. The convergence of the algorithm is proven using a discrete Lyapunov function. Simulation results are provided for illustration.*

Keywords: *Active noise control; neural network; saturation compensation; filtered-X least-mean-square algorithm; convergence*

1. INTRODUCTION

ANC has received much attention 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 acoustic and electrical control basis of ANC system is introduced in [1]. The filtered-x least mean square (FXLMS) algorithm is a popular adaptive filtering algorithm using a finite impulse response (FIR) filters [1, 2], because it is simple and has relatively low computational load. The development of digital signal processing (DSP) hardware allows more sophisticated algorithms to be implemented in real time to improve the system performance [3]. Linear ANC systems have been successfully used to cancel noise in air conditioning duct systems, handsets, and others [1-3]. However, in a practical ANC system, the secondary path and primary path of the ANC system may exhibit nonlinear behaviors. The ANC system has to be adaptive because of changes in environment, degradation of system components, and alteration of the noise source. The use of adaptive Volterra filter in ANC system has been presented in [4]. The main drawback of this approach is that the size of the filter increases exponentially with the number of inputs and the computation task is extremely heavy. The use of neural networks has been suggested to cope with the case of nonlinear system [5-8]. The major problem with an neural network based ANC is its relatively slow learning process. In references [9-15] fuzzy-neural and recurrent neural networks have also been used in nonlinear ANC system. 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 nonlinear acoustic path. A feedback neural network controller is proposed, where the model of neural network is simplified to meet the characteristic of an ANC system. The remainder of the paper is organized as follows. Section 2 describes the traditional nonlinear ANC system and its adaptive algorithm. In section 3, the proposed ANC system is presented. Section 4 analyses the convergence of the proposed algorithm using a discrete Lyapunov function. Section 5 presents simulation results to illustrate the proposed ANC system. The conclusions are given in section 6.

2. TRADITIONAL ANC SYSTEM

The traditional adaptive feedback ANC system using neural network is presented Fig. 1. In Fig.1, the primary noise x(k), generated by the noise source, propagates through the primary path *P(z)*. The secondary noise y(k), generated by the ANC system, propagates through the secondary path *G(z)* and *S(v)*, where *S(v)* stands for the saturation of the ANC system. The primary noise and the secondary noise are combined to produce the residual noise, e(k) = d(k) + v(k), in the region where the noise is to be controlled. A microphone is placed in this region to measure the residual noise e(k).

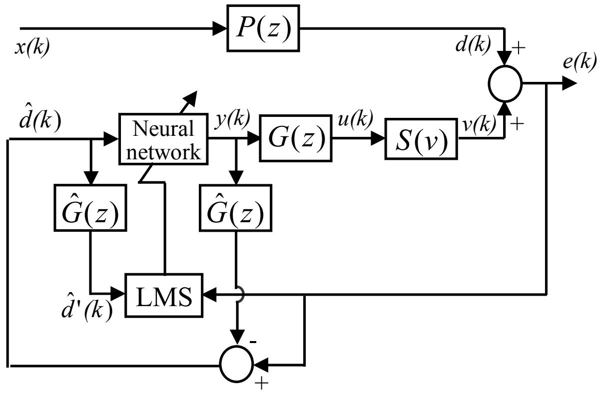


Fig. 1. Adaptive feedback ANC system

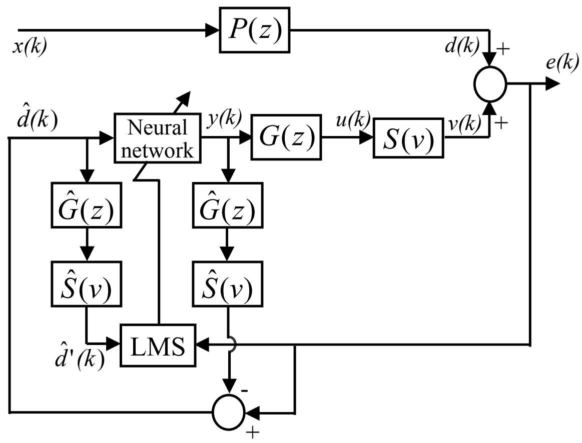


Fig. 2. The proposed ANC system with saturation compensation

The neural network is used to produce the secondary noise y(k). It is trained such that the residual noise e(k) is minimized. The introduction of the secondary-path transfer function in the system using the LMS algorithm may lead to instability. This is because, it is impossible to compensate for the inherent delay due to *G(z)* if the primary path *P(z)* does not contain a delay of equal length. Also, a very large FIR filter would be required to effectively model *1/G(z)*. This can be solved by placing a model $\hat{G}(z)$ of the secondary path *G(z)* in the reference signal path to the weight update of the LMS equation. Note that *G(z)* includes the digital-to-analog converter, reconstruction filter, power amplifier, loudspeaker, acoustic path from loudspeaker to residual noise, preamplifier, anti aliasing filter, and analog-to-digital converter.

3. THE PROPOSED ANC SYSTEM

The proposed feedback ANC system is presented in Fig. 2, where $\hat{S}(v)$ is a model of *S(v)* and is used to compensate for the saturation of the power amplifier. The ANC system can be described by the following equations:

The residual noise is given by

$$e(k) = d(k) + v(k) \tag{1}$$

The secondary noise can be approximated as

$$v(k) = \frac{2}{1 + e^{-\lambda u(k)}} - 1 \tag{2}$$

where the tansig function is used to describe the saturation of the system

$$u(k) = G(z)y(k) = \sum_{m=0}^{M} g(m)y(k-m)$$

The neural network

$$y(k) = f(net(k)) = net(k), \tag{3}$$

(linear activation function), and

$$net(k) = \sum_{j=1}^{m} w_{ij}\hat{d}_j(k) = W(k)^T D(k) \tag{4}$$

(linear integration function)

where *W(k)* represents a column vector of all of the network weights and *D(k)* represents the input signal, k is the time index and f is the activation function,

$$W(k) = \begin{bmatrix} w_0(k) & w_1(k) & \dots & w_{L-1}(k) \end{bmatrix}^T,$$
$$D(k) = \begin{bmatrix} \hat{d}(k) & \hat{d}(k-1) & \dots & \hat{d}(k-n) \end{bmatrix}^T$$

Define the cost function as

$$V(k) = \tfrac{1}{2} e^2(k) = \tfrac{1}{2}[d(k) + v(k)]^2 \tag{5}$$

The network weights update is based on a stochastic steepest descent which incrementally reduces the instantaneous squared error in the output of the neural network as:

$$W(k+1) = W(k) - \eta \nabla V(k) = W(k) - \eta \left[\frac{\partial V(k)}{\partial W(k)} \right]^T \tag{6}$$

where η is the learning rate. Applying the chain rule to (6):

$$\frac{\partial V}{\partial W} = \frac{\partial V}{\partial e}\frac{\partial e}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial W} = e\frac{\partial v}{\partial u}\frac{\partial u}{\partial W} \tag{7}$$

From (2), we obtain

$$\frac{\partial v}{\partial u}=\frac{2\lambda e^{-\lambda u(k)}}{\left[1+e^{-\lambda u(k)}\right]^2}=\frac{2\lambda\left[\dfrac{1-v(k)}{1+v(k)}\right]}{\left[\dfrac{2}{1+v(k)}\right]^2}=\tfrac{\lambda}{2}[1-v(k)][1+v(k)]=\tfrac{\lambda}{2}[1-v^2(k)] \tag{8}$$

From (3) and (4), $\dfrac{\partial u}{\partial W}=\left[\sum_{m=0}^{M}\dfrac{\partial u}{\partial y}\dfrac{\partial y}{\partial W}\right]^T=\left[\sum_{m=0}^{M}g(m)\hat{d}(k-m)\right]^T$

where *g(m)* are the coefficients of the *Mth* order FIR filter *G(z)*. Thus, according to (6), the network weights update is computed as

$$W(k+1)=W(k)-\tfrac{1}{2}\eta\lambda e(k)[1-v^2(k)]\sum_{m=0}^{M}g(m)\hat{d}(k-m) \tag{9}$$

4. CONVERGENCE OF THE PROPOSED ANC SYSTEM

Let *V(k)* as (5) be the discrete-type Lyapunov function candidate. Due to the training process, we have

$$\begin{aligned}\Delta V(k)&=V(k+1)-V(k)=\tfrac{1}{2}[e^2(k+1)-e^2(k)]\\&=\tfrac{1}{2}[e(k+1)-e(k)][e(k+1)+e(k)]=\tfrac{1}{2}\Delta e(k)[2e(k)+\Delta e(k)]\end{aligned} \tag{10}$$

The error difference resulting from the learning can be represented by

$$\begin{aligned}\Delta e(k)&=e(k+1)-e(k)=\left[\frac{\partial e}{\partial W}\right]^T\Delta W(k)=\left[\frac{\partial e}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial y}\frac{\partial y}{\partial W}\right]^{T^T}\Delta W(k)\\&=\left[\tfrac{\lambda}{2}\left(1-v^2(k)\right)\sum_{m=0}^{M}g(m)\hat{d}(k-m)\right]^T\times\left[-\tfrac{\lambda}{2}\eta e(k)\left(1-v^2(k)\right)\sum_{m=0}^{M}g(m)\hat{d}(k-m)\right]\\&=-\tfrac{1}{4}\eta\lambda^2 e(k)[1-v^2(k)]^2A^2(k)\end{aligned} \tag{11}$$

where $A(k)=\sum_{m=0}^{M}g(m)\hat{d}(k-m)$

It follows from (11) that

$$\begin{aligned}\Delta V(k)&=-\tfrac{1}{8}\eta\lambda^2 e(k)[1-v^2(k)]^2A^2(k)\times\left\{2e(k)-\tfrac{1}{4}\eta\lambda^2 e(k)[1-v^2(k)]^2A^2(k)\right\}\\&=-\tfrac{1}{8}\eta\lambda^2 e^2(k)[1-v^2(k)]^2A^2(k)\times\left\{2-\tfrac{1}{4}\eta\lambda^2[1-v^2(k)]^2A^2(k)\right\}\end{aligned}$$

If the learning rate η is chosen as

$$0<\eta<\frac{8}{\lambda^2[1-v^2(k)]^2A^2(k)} \tag{12}$$

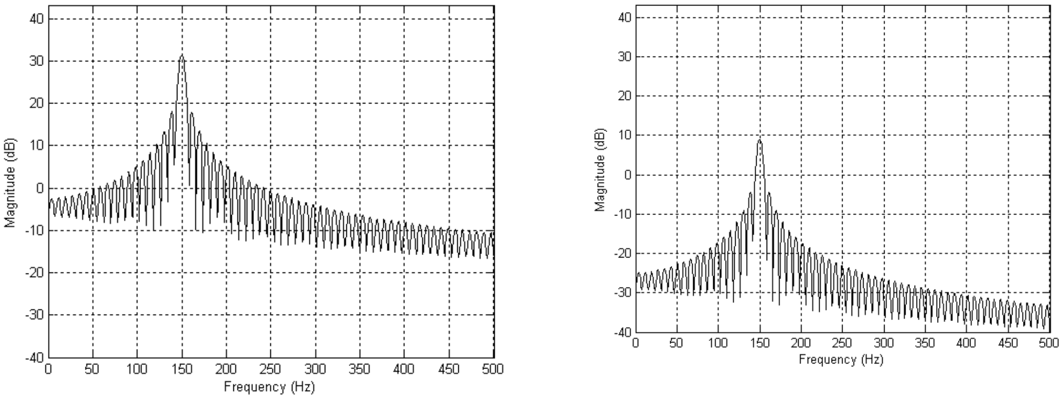
then $\Delta V(k) < 0$. Therefore, the control system is locally convergent.

5. SIMULATION RESULTS

In the following simulations, the noise source is a sinusoidal signal of frequency 150Hz. The sampling frequency is chosen to be 8-KHz, the saturation level is ±0.5, the learning rate for W is chosen as $\eta = 1$.

An ANC example is selected to illustrate the effectiveness of the adaptive feedback ANC system using neural network (NN). In oder to see the amount of attenuation, the result of canceling noise is shown in frequency domain. Fig. 3(a) is the primary noise. Fig. 3(b) is the noise canceling results by the NN algorithms.

It is clear that the proposed ANC system performs excellently in canceling the periodic signal. The attentuation of periodic noise is about 20dB for the conventional NN method.



(a) (b)

Fig. 3. ANC of periodic noise: (a) primary noise, (b) ANC with NN

Fig. 4 and Fig. 5 show, respectively, the simulation results of neural network ANC system with and without saturation compensation. Remark that, without saturation compensation, the ANC system can not operates effectively (Fig. 3) when the noise level is high; with saturation compensation, the ANC system operates effectively (Fig. 4) even when the noise level is high.

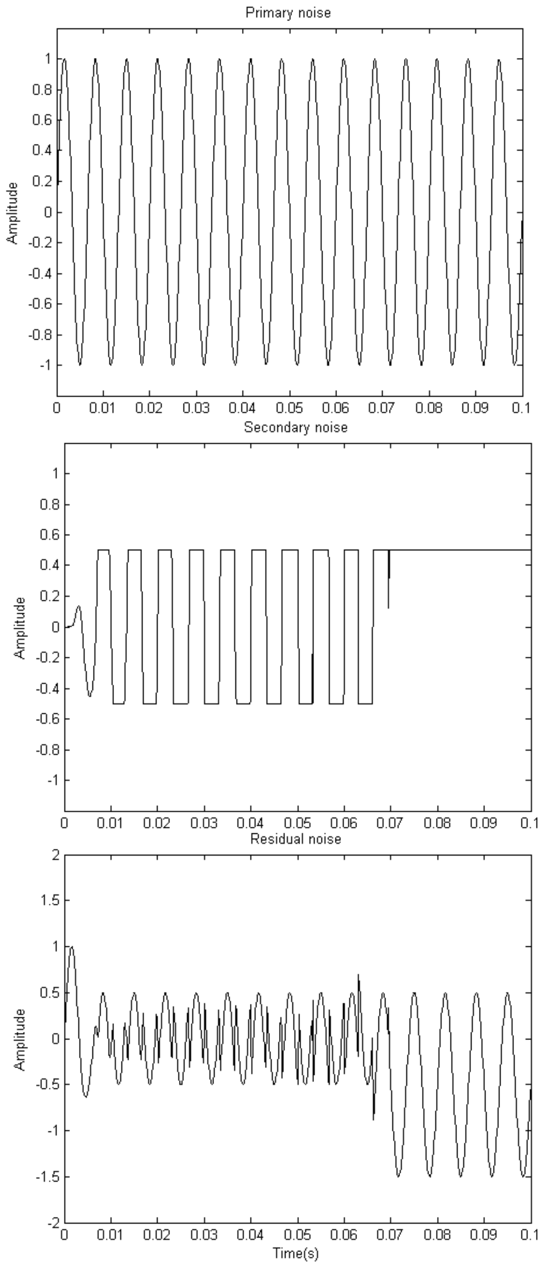


Fig. 4. NN ANC system without saturation compensation

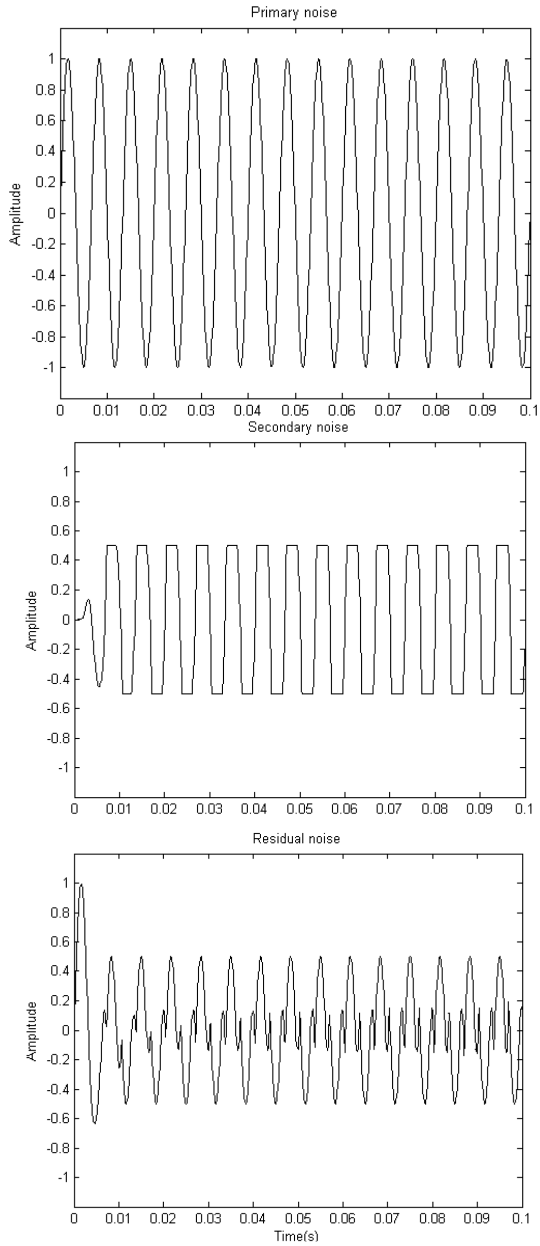


Fig. 5. NN ANC system with saturation compensation

6. CONCLUSIONS

This paper presents an ANC system using neural network. The saturation of the power amplifier is compensated. The convergence of the proposed algorithm is proven using a discrete Lyapunov function. Computer simulations show that the proposed system is effective. The proposed algorithm is also versatile and can be used in other applications. Results in real system as well as the case of multiple noise sources will be presented in a near future.

HỆ THỐNG KIỂM SOÁT NHIỄU TÍCH CỰC HỒI TIẾP DÙNG MẠNG NƠRON

Huỳnh Văn Tuấn[(1)], Nguyễn Hữu Phương[(1)], Nguyễn Ngọc Long[(2)]
(1) Trường Đại học Khoa học Tự Nhiên, ĐHQG-HCM
(2)Trường Đại học Tôn Đức Thắng

TÓM TẮT: *Bài báo này thực hiện giải thuật FxLMS (Filtered-x Least Mean Square) trên cơ sở mạng nơron nhân tạo để kiểm soát nhiễu tích cực (ANC). Vấn đề bão hòa của bộ khuếch đại công suất trong hệ thống ANC được trình bày. Phương pháp bổ chính bão hòa và giải thuật học trực tuyến dựa trên phương pháp giảm độ dốc được thực hiện. Điều kiện hội tụ được chứng minh bằng cách sử dụng hàm Lyapunov rời rạc. Các kết quả mô phỏng được trình bày.*

Từ khóa: *Kiểm soát nhiễu tích cực; mạng nơron; bổ chính bão hòa; giải thuật FxLMS; hội tụ.*

REFERENCES

[1]. S.J. Elliott, P.A. Nelson, Active noise control, IEEE Signal Process Magazine 10, 1993, pp. 12-35.

[2]. S. M. Kuo and D. R. Morgan, Active noise control: A tutorial review, Proc. IEEE, Vol. 87, No. 6, June 1999.

[3]. Huynh Van Tuan, Master thesis, University of Natural Sciences, National University – HCMC, 2004.

[4]. L. Tan, J. Jiang, Adaptive volterra filters for active noise control of nonlinear filters-Neural filters, IEEE Trans. On Signal Processing 49, 2001, pp. 1667-1676.

[5]. Gary G. Yen, Frequency-domain vibration control using adaptive neural network, IEEE, 1997.

[6]. M. Bouchard, New recursive-least-squares algorithms for nonlinear active noise control of sound and vibration using neural networks, IEEE Trans. on neural network, Vol. 12, No. 1, January 2001.

[7]. M. Bouchard, B. Paillard, and C. T. L. Dinh, Improved training of neural networks for the nonlinear active control of sound and vibration, IEEE Trans. on neural network, Vol. 10, No. 2, March 1999.

[8]. J. Canfield, L. G. Kraft, P. Latham, and A. Kun, Filtered-X CMAC: An efficient algorithm for active disturbance cancellation in nonlinear dynamical systems, University of New Hampshire Durham, NH 03824.

[9]. G. Chen, T. Sone, The stability and convergence characteristics of the delayed-X LMS algorithm in ANC systems, Journal of Sound and Vibration (1998) 261(4), pp. 637-648.

[10]. R. Jha and C. He, Adaptive neurocontrollers for vibration suppession of nonlinear and time varying structures, Journal of Intelligent Material Systems and Structures, Vol.15, Sep./Oct. (2004).

[11]. Q.Z. Zhang, W.S. Gan, Y.L. Zhou, Adaptive recurrent fuzzy neural networks for active noise control, Journal of Sound and Vibration 296, 2006, pp. 935-948.

[12]. Q.Z. Zhang, W.S. Gan, Active noise control using a simplified fuzzy neural netwok, Journal of Sound and Vibration 272, 2004, pp. 427-449.

[13]. C.Y. Chang, F.B. Luoh, Enhancement of active noise control using neural-based filtered-X algorithm, Journal of Sound and Vibration 305 (2007) 348-356.

[14]. C. Li, K.H. Cheng, Recurrent neuro-fuzzy hybrid-learning approach to accurate system modeling, Fuzzy Sets and Systems 158, 2007, pp. 194-212.

[15]. Q. Wenzhong, S. Jincai, Q. Yang, Active control of vibration using a fuzzy control method, Journal of Sound and Vibration 275, 2004, pp. 917-930.

[16]. Duong Hoai Nghia, Huynh Van Tuan, Active noise control using neural system, The International Symposium On Electrical-Electronic Engineering (ISEE), Oct.24-25, University of Technology-HoChiMinh city, Vietnam, 2007.