ACTIVE NOISE CONTROL USING NEURAL SYSTEM

Huynh Van Tuan(1)**, Duong Hoai Nghia**(2)

(1) University of Science, VNU-HCM

(2) University of Technology, VNU-HCM

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ABSTRACT: *The principle of active noise control (ANC) is to produce a secondary acoustic noise which has the same magnitude as the unwanted primary noise but with opposite phase. The sum of these two signals reduces acoustic noise in the noise control area. In this paper we present a new ANC method using neural system. Moreover a new method for compensating the saturation of the power applifier is also introduced. The performance of the proposed method is compared to that of traditional methods. Simulation results are provided for illustration.*

Keywords*: ANC, neural system*

1. INTRODUCTION

Acoustic noise problems become more and more evident as increased numbers of industrial equipment such as engines, blowers, fans, transformers, and compressors are in use. Traditional methods of acoustic noise control use passive controls such as enclosures, barriers, and silencers to attenuate the undesired noise [1], [2]; however, they are relatively large, costly, and ineffective at low frequencies [1], [3]. The ANC system efficiently attenuates low frequency noise where passive methods are either ineffective or tend to be very expensive or bulky.

Adaptive linear filtering techniques have been extensively used for the ANC, and many of today's implementations of active noise control use those techniques [1]-[3]. A popular adaptive filtering algorithm is the filtered-X Least Mean Square (LMS) algorithm, because of its simplicity and its relatively low computational load [1], [2], [7], [8]. This algorithm is a steepest descent algorithm that uses an instantaneous estimate of the gradient of the cost function. Detailed presentations of ANC can be mentioned as follows: [2] considers a frequency-domain approach using adaptive neural network; [4] proposes a recursive-least-squares algorithm for nonlinear ANC system using neural networks; [5] uses a neural network for the nonlinear active control of sound and vibration; [6] presents a filtered-X CMAC algorithm for active disturbance cancellation in nonlinear dynamical systems; [7] introduces a stable adaptive IIR filter for active noise control systems; [8] investigates stability and convergence characteristics of the delayed-X LMS algorithm in ANC systems; [9] presents an adaptive neurocontrollers for vibration suppession of nonlinear and time varying structures; [10] proposes an intelligent active vibration control for a flexible beam system. etc.

ANC using neural system is considered in this paper. Neural network based adaptive control systems with online learning are capable of updating the weights of the filtered-X LMS algorithm. And, ANC is based on feedback control, where the active noise controller attempts to cancel the noise without the benefit of an upstream reference input, which will be dicussed in section 2 and section 3 .

2. TRADITIONAL ANC SYSTEMS

2.1. Feedforward ANC system

The block diagram of a feedforward ANC system using the filtered-X LMS algorithm is illustrated in Fig. 1, in which an adaptive filter $W(z)$ is used to estimate the unknown plant $P(z)$. The primary path $P(z)$ consists of the acoustic response from the micro 1 to micro 2 where the primary noise is combined with the output of the adaptive filter. Therefore, it is necessary to compensate for the secondary-path transfer function $G(z)$ from *y(n)* to *e(n)*, which includes the digital-to-analog converter, reconstruction filter, power amplifier, loudspeaker, acoustic path from loudspeaker to micro 2, pre-amplifier, anti-aliasing filter, and analog-to-digital converter.

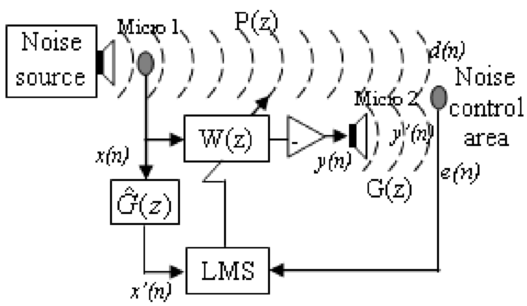

Fig. 1. Feedforward ANC system using the FXLMS algorithm

The introduction of the secondary-path transfer function in a system using the standard LMS algorithm leads to instability 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 an identical filter $\hat{G}(z)$ in the reference signal path to the weight update of the LMS equation.

The secondary signal *y(n)* is computed as

$$y(n) = \underline{w}^T(n)\underline{x}(n) \qquad (1)$$

where

$\underline{w}(n) = [w_0(n) \quad w_1(n) \quad \Lambda \quad w_L(n)]^T$

and $\underline{x}(n) = [x(n) \quad x(n-1) \quad \Lambda \quad x(n-L)]^T$ are the coefficient and signal vectors, respectively, of W(z) and L is the filter order.

The FXLMS algorithm updates the coefficient vector

$$\underline{w}(n+1) = \underline{w}(n) + \mu \underline{x}'(n)e(n) \qquad (2)$$

where $\underline{x}'(n) = \hat{g}(n) * \underline{x}(n)$, $\hat{g}(n)$ is the impulse response of the estimated secondary-path filter $\hat{G}(z)$, and (*) denotes the convolution operator.

2.2. Feedback ANC system

In many applications, it is not feasible to measure the primary noise and we have to use a feedback ANC system (Fig. 2).

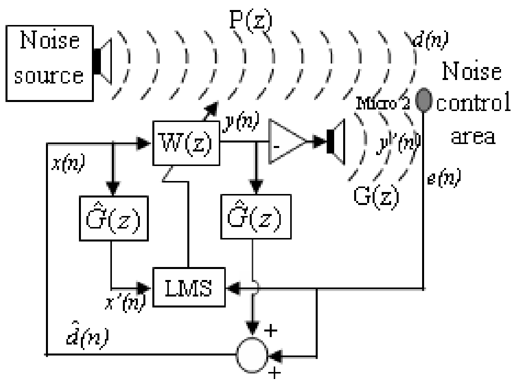

Fig. 2. Feedback ANC system using the FXLMS algorithm

The basic idea of adaptive feedback ANC is to estimate the primary noise and use it as a reference signal x(n) for the ANC filter. In Fig. 2, the primary noise is expressed in the z-domain as

$$\hat{D}(z) = E(z) + \hat{G}(z)Y(z) \qquad (3)$$

where $E(z)$ is the signal obtained from the error sensor and $Y(z)$ is the secondary signal generated by the adaptive filter W(z). If $\hat{G}(z) \approx G(z)$, we can estimate the primary noise $d(n)$ and use this as a synthesized reference signal $x(n)$. That is

$$X(z) \approx \hat{D}(z) = E(z) + \hat{G}(z)Y(z) \qquad (4)$$

or in the time domain

$$x(n) \approx \hat{d}(n) = e(n) + \sum_{m=0}^{M} \hat{g}_m y(n-m) \qquad (5)$$

where $\hat{g}_m, m = 0, 1, ..., M$, are the coefficients of the Mth order FIR filter $\hat{G}(z)$ used to estimate the transfer function of the secondary path. The algorithm for feedback ANC is similar to (1), (2).

3. NEURAL NETWORK BASED FEEDBACK ANC SYSTEM

In order to cope with the nonlinearity in the system, we propose to replace the FIR filter W(z) in figure 2 by a perceptron with linear integration function

$$net = \sum_{j=0}^{L} w_j(n)x(n\text{-}j) = \underline{w}^T(n)\underline{x}(n) \qquad (6)$$

and tansig activation function

$$y(n) = f(net) = \frac{2}{1+e^{-net}} - 1 \qquad (7)$$

(Fig. 3), where $\underline{w}(n)$ is the weight vector and $\underline{x}(n)$ is the regressor

$$\underline{w}(n) = \begin{bmatrix} w_0(n) \\ w_1(n) \\ \mathrm{M} \\ w_{L-1}(n) \end{bmatrix}, \quad \underline{x}(k) = \begin{bmatrix} x(n) \\ x(n-1) \\ \mathrm{M} \\ x(n-L) \end{bmatrix} \qquad (8)$$

Define the cost function as

$$J(n) = \frac{1}{2}e^2(n) \qquad (9)$$

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

$$\underline{w}(n+1) = \underline{w}(n) - \eta\left[\frac{\partial J(n)}{\partial \underline{w}(n)}\right]^T \qquad (10)$$

where $\eta > 0$ is the gain parameter. Applying the chain rule

$$\frac{\partial J(n)}{\partial \underline{w}} = \frac{\partial J(n)}{\partial e}\frac{\partial e}{\partial \underline{w}} \qquad (11)$$

Since

$$J(n) = \frac{1}{2}e^2(n) \Rightarrow \frac{\partial J(n)}{\partial e} = e(n);$$

$$e(n) = d(n) - y'(n) = d(n) - \sum_{m=0}^{M} g_m y(n-m) \Rightarrow \frac{\partial e}{\partial \underline{w}} = -\sum_{m=0}^{M} g_m \frac{\partial y(n-m)}{\partial \underline{w}}$$

$$\frac{\partial y(n-m)}{\partial \underline{w}} = \frac{\partial y(n-m)}{\partial net}\frac{\partial net}{\partial \underline{w}} = \frac{1}{2}[1-y^2(n-m)]\underline{x}(n-m)^T$$

where the last equality follows from (6) and (7). We have

$$\frac{\partial J(n)}{\partial \underline{w}} = -\frac{1}{2}e(n)\sum_{m=0}^{M} g_m[1-y^2(n-m)]\underline{x}(n-m)^T \qquad (12)$$

Thus the network weights update is computed as

$$\underline{w}(n+1) = \underline{w}(n) + \frac{1}{2}\eta e(n)\sum_{m=0}^{M} g_m[1-y^2(n-m)]\underline{x}(n-m)^T \qquad (13)$$

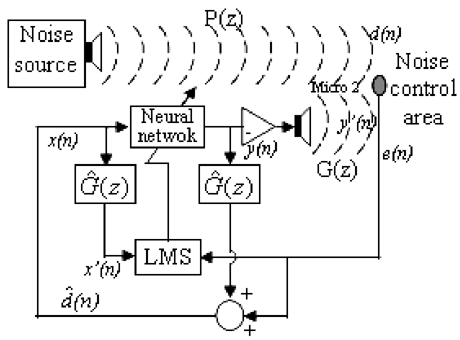

Fig. 3. Neural network based feedback ANC system

Remark that if we use the linear activation function then

$$y(n) = f(net) = net = \underline{w}^T(n)\underline{x}(n) \qquad (14)$$

we have the system of Fig. 2. So the difference between the system in Fig. 2 and the proposed system in Fig. 3 is that we use the activation function (9) to take into account the nonlinearity in the system.

4. SATURATION COMPENSATION

In order to compensate for the saturation of the power amplifier, we introduce the saturation blocks $S(v)$ as in Fig. 4

$$S(v) = \begin{cases} 1, & 1 < v \\ v, & -1 \le v \le 1 \\ -1, & v < -1 \end{cases} \qquad (15)$$

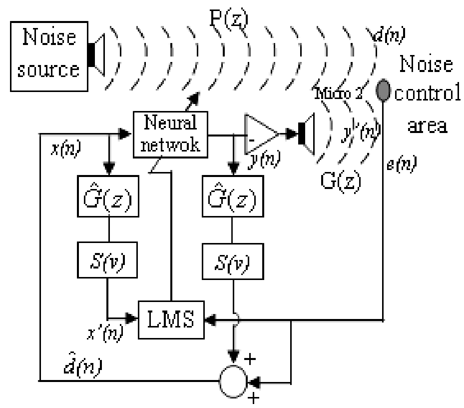

Fig. 4. Neural network ANC system with saturation compensation

5. SIMULATION RESULTS

In the following simulations, the noise source is a sinusoidal signal of frequency 150Hz. The sampling rate is 8 KHz.

5.1. Traditional feedback ANC system

Fig. 5 and Fig. 6 show, respectively, the simulation results of traditional ANC system with and without saturation compensation. Remark that without saturation compensation the system can not function when the power amplifier is saturated. With saturation compensation, system still functions even when the power amplifier is saturated.

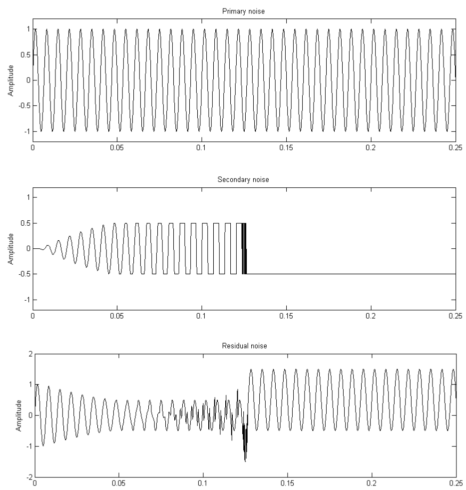

Fig. 5. Traditional ANC system without saturation compensation

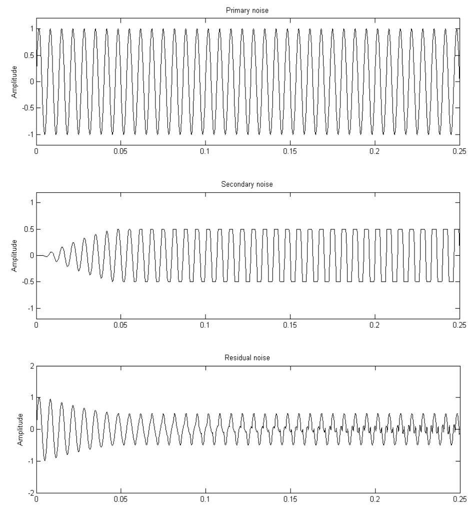

Fig. 6. Traditional ANC system with saturation compensation

5.2. Neural network based feedback ANC system

Fig. 7 and Fig. 8 show, respectively, the simulation results of neural network ANC system with and without saturation compensation. Fig. 9 and Fig. 10 show the zoom of Fig. 7 and Fig. 8, respectively. Remark that the ANC system with saturation compensation is much more effective than the ANC system without saturation compensation.

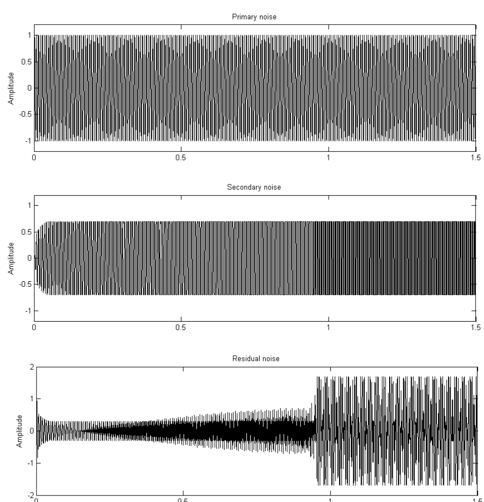

Fig. 7. Neural network ANC system without saturation compensation

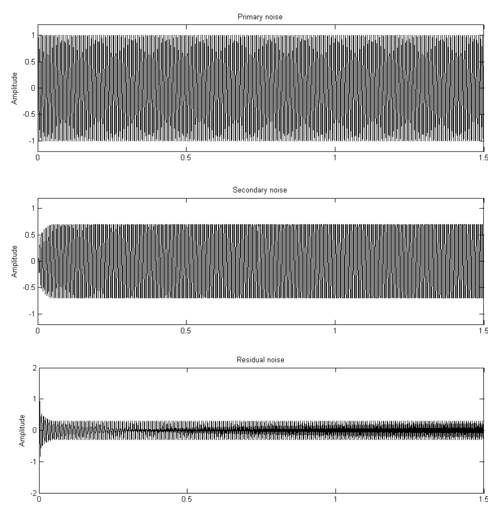

Fig. 8. Neural network ANC system with saturation compensation

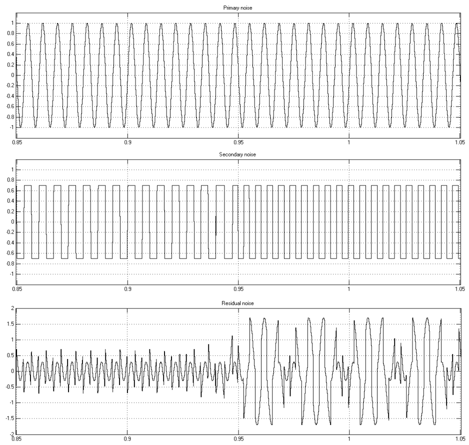

Fig. 9. Zoom of Fig. 7.

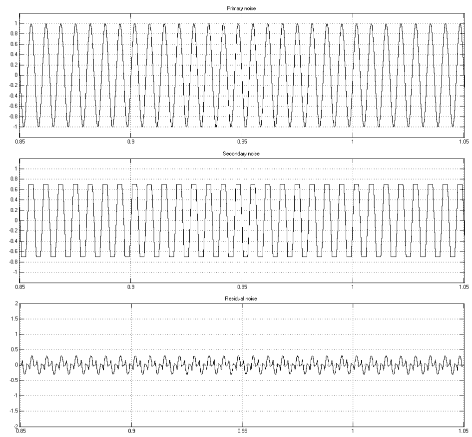

Fig. 10. Zoom of Fig. 8.

6. CONCLUSIONS

This paper deals with ANC systems. The contribution of the paper is twofold. Firstly, to cope with the nonlinearity in the system, we investigate the use of a feedforward neural network to replace the traditional FIR filter in the forward branch. Secondly we propose a method for saturation compensation. Simulation results show that the proposed system is effective.

KIỂM SOÁT TIẾNG ỒN TÍCH CỰC DÙNG MẠNG NƠRON

Huỳnh Văn Tuấn[(1)], Dương Hoài Nghĩa[(2)]

(1) Trường Đại học Khoa học Tự Nhiên, Đại học Quốc Gia Tp.HCM

(2) Trường Đại học Bách Khoa, Đại học Quốc Gia Tp.HCM

TÓM TẮT: *Nguyên lý của kiểm soát tiếng ồn tích cực là tạo ra tiếng ồn thứ cấp có cùng biên độ nhưng ngược pha với tiếng ồn sơ cấp sao cho tiếng ồn tổng hợp giảm đi trong môi trường kiểm soát tiếng ồn. Trong bài bài báo này chúng tôi giới thiệu một phương pháp kiểm soát nhiễu mới sử dụng mạng nơron. Chúng tôi cũng đã đưa ra một phương pháp mới về bổ chính bão hòa của bộ khuếch đại công suất trong hệ thống kiểm soát tiếng ồn. Giải thuật kiểm soát tiếng ồn đưa ra được so sánh với các giải thuật truyền thống. Các kết quả mô phỏng được trình bày.*

Từ khóa: *kiểm soát tiếng ồn, mạng nơron.*

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