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Short Communication

Enhancement of active noise control using neural-based filtered-X algorithm ☆

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Abstract

This paper presents a neural-based filtered-X least-mean-square algorithm (NFXLMS) to cancel the nonlinear broadband noise in an active noise control (ANC) system. The ways to avoid the premature saturation of backpropagation algorithm and to design the optimal learning rate are also included in the paper to improve the noise reduction performance. Besides, the proposed neural filter can be easily implemented and versatile to the other applications. Several simulation results show that the proposed method can effectively cancel the narrowband and nonlinear broadband noise in an ANC system.

1. Introduction

Noise is annoying to most people in many occasions. Fans, engines, machine tools, and automated manufacturing equipments may generate acoustic levels up to 120 dB. These industrial noises often have the significant power in the low-frequency range (e.g. under 500 Hz). However, the conventional passive control methods, suppressing acoustic noise using sound-absorbing materials, generally do not work well at low frequency. This is because the thicknesses of the absorbers are not large enough, when compared to the acoustic wavelength at low frequency. Besides, it is also difficult to reduce low-frequency sound being transmitted from one space to another space unless the intervening barrier is very heavy. For these reasons, passive schemes cannot control low-frequency noise well. Besides, the back pressure, arousing by using absorber, will also deteriorate the system performance. Hence, the active noise control (ANC) systems, which do not use any sound-absorbing material, have received a lot of attention in recent years.

The ANC system uses the principle of acoustic superposition to achieve the attenuation of the unwanted sound. It involves an electro-acoustic system that cancels the primary (unwanted) noise; specifically, an anti-noise of equal amplitude and opposite phase is generated and combined with the primary noise, thus resulting in the cancellation of both noises. The ANC has to be adaptive because of changes in environment, degradation of system components, and alteration of the noise source [1]. Methods of actively controlling

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noise include both feedback and feedforward controls [2,3]. Feedback control uses a feedback signal as a reference input to an active noise controller, which is obtained from an error microphone, e.g., at the open end of a duct. Feedforward control uses anti-noise, which is correlated with the original noise, to cancel the noise. The primary advantage of feedback control is that no additional reference input is required, so the acoustic feedback problem is prevented. However, feedback control suffers from the ''waterbed'' effect because of time delays and non-minimum phase zeros; only narrowband noise reduction can thus be achieved. For a high-order model, such as a duct, feedforward control appears to be a viable method for reducing noise at the expense of robustness of performance against plant uncertainty [4].

Most of the conventional ANCs, employing the standard filtered-X least-mean-square (FXLMS) algorithm, are linear in nature [5,6]. However, the FXLMS algorithm is not capable of training a nonlinear controller, since this algorithm exploits the linearity of the controller. So, active control of nonlinear noise is hard to achieve. Some papers have investigated this problem. A normalized Gaussian radial basis function neural network is proposed to compensate the non-minimum phase secondary path transfer function and control the nonlinear noise process in Ref. [1]. In Ref. [7], the authors introduced the adaptive Volterra filters for feedforward ANC based on multichannels structure. In Refs. [8–11] fuzzy-neural and recurrent neural networks have also been used to control the nonlinear noises in the ANC system. Observing the various methods presented in past years, it reveals that the ANC structures for nonlinear control are complex or hard to realize [12]. Keeping these in view, the authors propose the neural-based filtered-X least-mean-square (NFXLMS) algorithm to control the nonlinear noise. This method can also avoid the premature saturation of backpropagation; meanwhile, achieve minimum error by using the proposed optimum learning rate. The paper is organized as follows. Section 2 describes the neural-based filtered-X algorithm. The designing procedures of the adaptive algorithm and learning rate are also presented. Section 3 presents several results to illustrate the improvement of the NFXLMS ANC system relative to the FXLMS method. Section 4 is a concluding summary.

2. The NFXLMS algorithm

In general, the ANC system is designed on the basis of a mathematical description and its linearized model. It can be suitably tuned to its desired response using the well-known FXLMS algorithm. However, this method is only effective in canceling narrowband noise but cannot provide adequate performance in broadband noise cancellation. The authors propose the neural-based ANC system, shown in Fig. 1 to be an alternative.

The architecture of the proposed neural filter is depicted in Fig. 2, where the parameter $w_{ij}(k)$ is the weight between the input layer and hidden layer ($i = 1,2,\ldots,n_1$, $j = 1,2,\ldots,n_2$), $v_j(k)$ is the weight between the hidden layer and output layer. Thus, $h_j(k)$, the output of the hidden node will be

$$h_j(k) = f_h(\mathrm{net}_j) = f_h\left(\sum_{i=1}^{n_1} w_{ij}(k)x(k-i+1)\right), \tag{1}$$

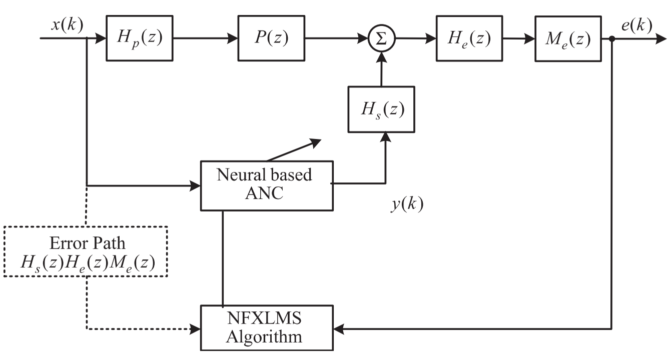

Fig. 1. Neural-based ANC system with NFXLMS algorithm.

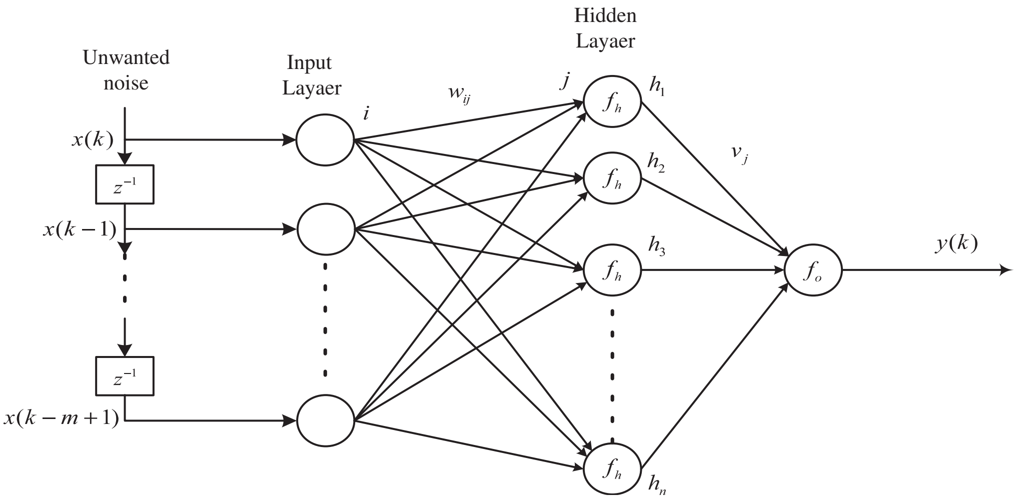

Fig. 2. Architecture of the neural filter.

where f_h is the activation function of the hidden node, and output of the output node $y(k) = f_o(\text{net}_o)$, with f_0 being the activation function

$$y(k) = f_o(\text{net}_o) = f_o\left(\sum_{j=1}^{n_2} h_j(k)v_j(k)\right). \tag{2}$$

The error function in ANC system to be minimized is defined as

$$E(k) = \tfrac{1}{2}(x(k)H_pPH_eM_e + y(k)H_sH_eM_e)^2. \tag{3}$$

In this paper, the backpropagation and the gradient descent methods are used to achieve the objective. The gradients of $v_j(k)$ and $w_{ij}(k)$ are shown in the following, respectively:

$$\frac{\partial E(k)}{\partial v_j(k)} = \frac{\partial E(k)}{\partial y(k)}\frac{\partial y(k)}{\partial \text{net}_o}\frac{\partial \text{net}_o}{\partial v_j(k)} = (e(k)H_sH_eM_e)f'_o(\text{net}_o)h_j(k), \tag{4}$$

$$\frac{\partial E(k)}{\partial w_{ij}(k)} = \frac{\partial E(k)}{\partial h_j(k)}\frac{\partial h_j(k)}{\partial \text{net}_j}\frac{\partial \text{net}_j}{\partial w_{ij}(k)} = e(k)H_sH_eM_ef'_o(\text{net}_o)v_j(k)f'_h(\text{net}_j)x(k-i+1), \tag{5}$$

hence, with η being the learning rate, we have

$$v_j(k+1) = v_j(k) - \eta e(k)H_sH_eM_ef'_o(\text{net}_o)h_j(k), \tag{6}$$

$$w_{ij}(k+1) = w_{ij}(k) - \eta e(k)H_sH_eM_ef'_o(\text{net}_o)v_j(k)f'_h(\text{net}_j)x(k-i+1). \tag{7}$$

In our discussions, $f_h(\text{net}_h) = \text{net}_h$ and $f_o(\text{net}_o) = \text{net}_o$ are used to prevent the processing units' saturation which might be induced by sigmoid or hyperbolic tangent functions. Those functions act as implicit constraints for the hidden node activations may get driven to their limits, making the resultant derivatives of saturated nodes very small due to $f'(\text{net})$. Hence, even with a sophisticated unconstrained optimization method, neural network learning might fail due to saturation. Therefore, Eqs. (6) and (7) can be expressed as follows respectively:

$$v_j(k+1) = v_j(k) - \eta e(k)H_sH_eM_eh_j(k), \tag{8}$$

$$w_{ij}(k+1) = w_{ij}(k) - \eta e(k)H_sH_eM_ev_j(k)x(k-i+1). \tag{9}$$

One can find $h_j(k)$ is also the function of $x(k)$, shown in Eq. (1). So, the correction terms in Eqs. (8) and (9) look like the output of error path with input $x(k)$. It is the so-called neural-based filtered-X LMS (NFXLMS) algorithm, which is different from the conventional FXLMS at the correction factors [13].

In order to achieve the optimal learning rate, one uses the Taylor series of the error functions:

$$e(k+1) = e(k) + \sum_{j=1}^{n_2} \frac{\partial e(k)}{\partial v_j(k)} \Delta v_j(k) + \sum_{i=1}^{n_1} \frac{\partial e(k)}{\partial w_{ij}(k)} \Delta w_{ij}(k) + \text{h.o.t.} \tag{10}$$

The partial differential terms in Eq. (10) can be represented by

$$\frac{\partial e(k)}{\partial v_j(k)} = \frac{\partial e(k)}{\partial y(k)} \frac{\partial y(k)}{\partial \text{net}_o} \frac{\partial \text{net}_o}{\partial v_j(k)} = H_s H_e M_e f'_o(\text{net}_o) h_j(k) = H_s H_e M_e h_j(k) \tag{11}$$

and

$$\begin{aligned} \frac{\partial e(k)}{\partial w_{ij}(k)} &= \frac{\partial e(k)}{\partial h_j(k)} \frac{\partial h_j(k)}{\partial \text{net}_j} \frac{\partial \text{net}_j}{\partial w_{ij}(k)} = H_s H_e M_e f'_o(\text{net}_o) v_j(k) f'_h(\text{net}_j) x(k-i+1) \\ &= H_s H_e M_e v_j(k) x(k-i+1). \end{aligned} \tag{12}$$

Thus,

$$\begin{aligned} e(k+1) &= e(k) + \sum_{j=1}^{n_2} H_s H_e M_e h_j(k)(-\eta e(k) H_s H_e M_e h_j(k)) \\ &\quad + \sum_{i=1}^{n_1} H_s H_e M_e v_j(k) x(k-i+1)(-\eta e(k) H_s H_e M_e v_j(k) x(k-i+1)) \\ &= e(k) \left\{ 1 - \eta \left[\sum_{j=1}^{n_2} (H_s H_e M_e h_j(k))^2 + \sum_{i=1}^{n_1} (H_s H_e M_e v_j(k) x(k-i+1))^2 \right] \right\} \end{aligned} \tag{13}$$

by excluding the h.o.t. of Eq. (10). In order to obtain an optimal learning rate of $\eta(k)$ to minimize $e(k+1)$; one can let

$$\eta_{\text{opt}}(k) = \left[\sum_{j=1}^{n_2} (H_s H_e M_e h_j(k))^2 + \sum_{j=1}^{n_1} (H_s H_e M_e \cdot v_j(k) \cdot x(k-i+1))^2 \right]^{-1}. \tag{14}$$

So, by choosing the η_{opt} in Eq. (14), one can minimize the residual noise $e(k)$.

3. Simulation results

The active control system and input signal are chosen to be representative of a simple ANC system for a duct. The duct model [14,15] is depicted as follows. The acoustic plant of duct $P(z)$ and $H_e(z)$ are modelled by pure time delays of 25 and 5 samples, respectively. Both the speakers, $H_p(z)$ and $H_s(z)$, and error microphone $M_e(z)$ are represented by the second-order Butterworth high-pass filters with a cutoff frequency of 80 Hz. The sampling frequency is chosen to be 2 kHz.

Thus, the duct plants are $P(z) = z^{-25}$ and $H_e(z) = z^{-5}$. They have no pole but only have zeros, $z = 0$. Besides, the characteristic of the second-order Butterworth high-pass filters with a cutoff frequency 80 Hz is $(0.8371 - 1.6742z^{-1} + 0.8371z^{-2})/(1 - 1.6475z^{-1} + 0.7009z^{-2})$, whose poles are $0.8237 \pm 0.15j$ and zeros are 1. So, all the poles and zeros of ANC plant are inside the unit circle, which implies the characteristics of the plants are minimum phase, causal, and stable.

Several different noise signals are used to verify the virtue of the proposed NFXLMS ANC system. All the initial weights, $w_{ij}(0)$ and $v_j(0)$, are randomly initialized between the range [−0.5, 0.5]. The proposed neural ANC filter is based on 4 input nodes, 6 hidden nodes and 1 output node neural network. The neural weighting parameters are all randomly chosen between [0, 1] at first and then the proposed NFXLMS algorithm will tune the free parameters adaptively to control the undesired noise. A 32nd-order adaptive FIR filter with zero initial weighting parameters and constant learning rate $\eta = 0.2$ is used to perform the FXLMS algorithm to be a contrast.

The first experiment uses a 200 Hz periodic signal as the undesired noise to illustrate the effectiveness of the proposed algorithm. Fig. 3 shows the result, solid line is the original periodic noise, the result of FXLMS algorithm is shown by dashed lines, and the proposed NFXLMS approach is shown by dotted line. One can find that both the conventional FXLMS and the proposed NFXLMS scheme cancel the unwanted noise well.

The next experiment uses the combination of 200- and 201-Hz periodic signals to be the undesired noise signal. Since the signal is composed of two periodic signals with close frequencies, the noise canceling result is interesting. In order to see the amount of attenuation, the result of canceling composite periodic signal is shown in frequency domain. Fig. 4(a) is the original composite periodic signal. Figs. 4(b) and (c) are the noise canceling results by the FXLMS and NFXLMS algorithms, respectively. It is clear that the proposed NFXLMS algorithm also performs excellently in canceling the composite periodic signals. Nevertheless, the conventional FXLMS algorithm cannot cancel the noise satisfactorily. The attenuation of composite periodic noise is about 30–50 dB by proposed neural method and is about 10 dB for the conventional FXLMS method.

Industrial broadband noise always has significant power below 800 Hz. So, we use a 0–800 Hz broadband white noise signal to be the unwanted noise in the third experiment. Besides, the result is also shown in frequency domain to see the amount of attenuation. Fig. 5(a) shows the nonlinear broadband noise. Fig. 5(b) shows the result of the noise cancellation by conventional FXLMS algorithm, from which one can see the ineffectiveness of the FXLMS in canceling broadband noise. However, one can see the effectiveness of NFXLMS in canceling the broadband noise as shown in Fig. 5(c). The performance of NFXLMS is about 10–15 dB; meanwhile, the conventional FXLMS cannot control the broadband noise at all.

The last experiment shows the enhancement of the proposed optimal learning rate $\eta_{\text{opt}}(k)$. Fig. 6 shows the performance of NFXLMS algorithm with $\eta_{\text{opt}}(k)$ and constant learning rate $\eta = 0.2$ for nonlinear broadband noise. One can find the mean square error by the proposed optimal learning rate converges faster than that of constant learning rate.

These results illustrate that the conventional FXLMS algorithm can only control the narrowband noise yet the proposed NFXLMS algorithm can cancel both the periodic and broadband noises well. The optimal learning rate also helps to achieve faster convergence of the proposed NFXLMS algorithm. Besides, the way to select the number of input node and hidden node is depicted as follows.

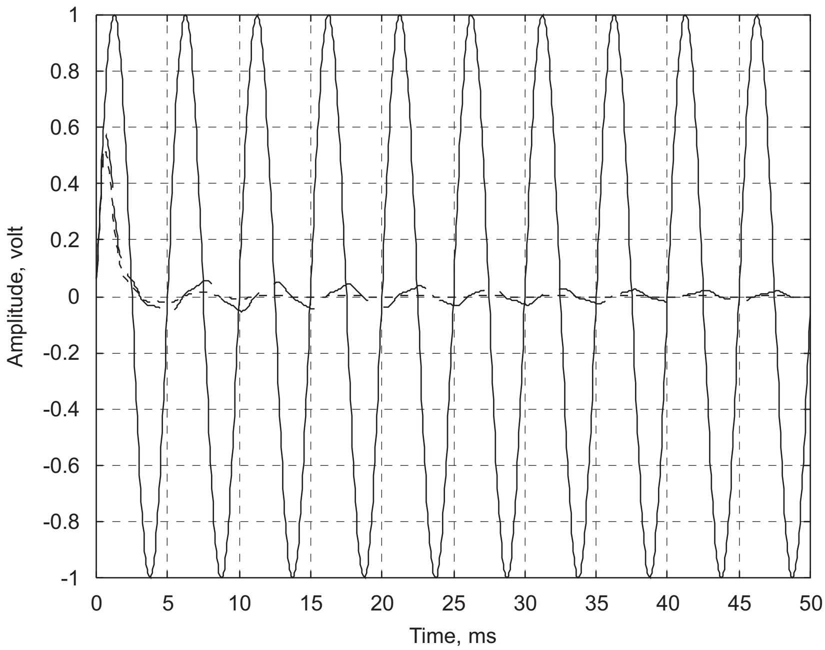

Fig. 3. ANC of periodic noise, original 200 Hz periodic noise: solid; ANC with FXLMS: dashed; ANC with NFXLMS: dotted.

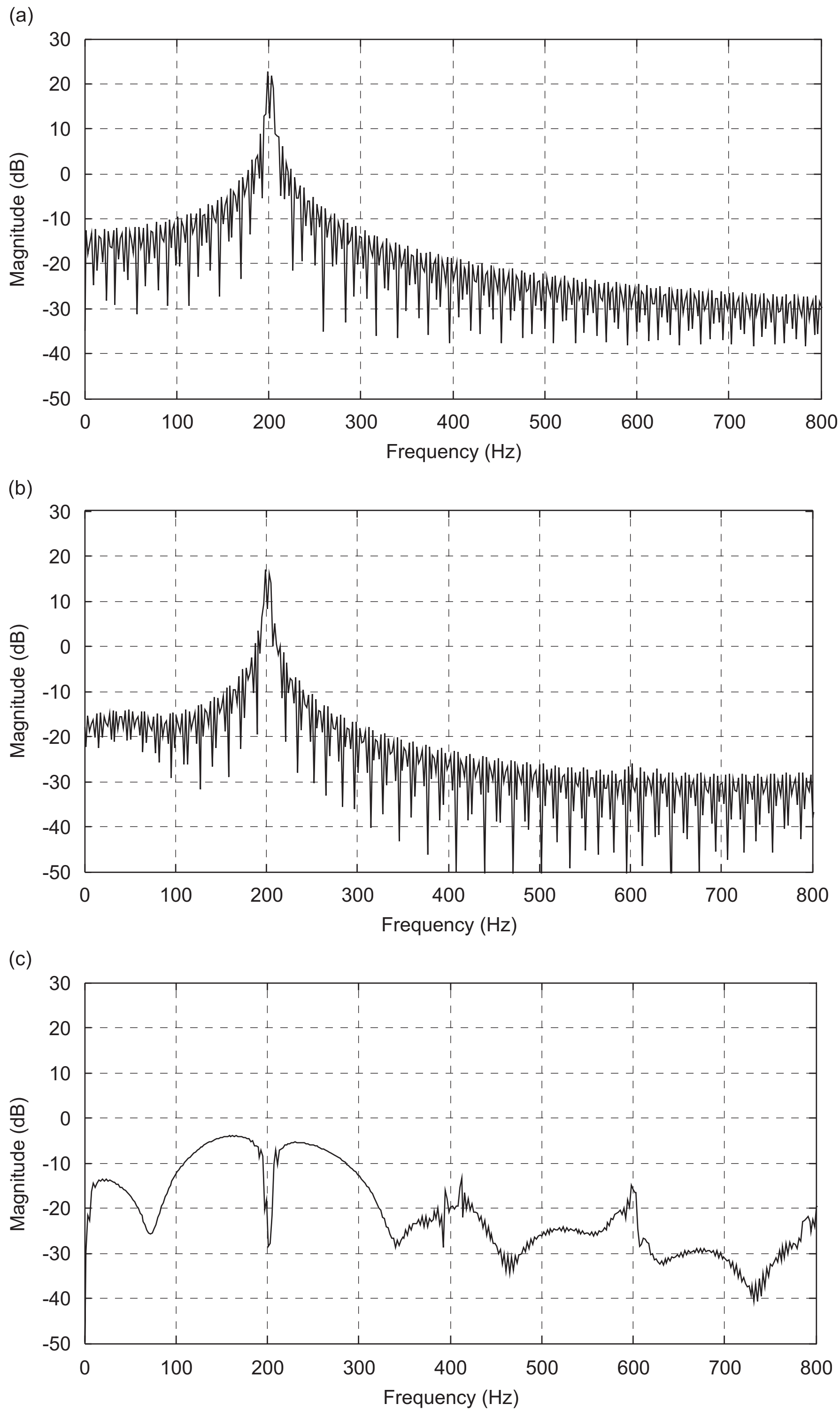

Fig. 4. ANC of composite periodic noise: (a) original composite periodic noise, (b) ANC with FXLMS, and (c) ANC with NFXLMS.

Too many input nodes and hidden nodes will raise the computing effort, which is not suitable for real-time control case. But too less input node and hidden node may also lead to the system inaccuracy. So, some studies suggest the number of hidden nodes should be within half to twice the number of input nodes by experience

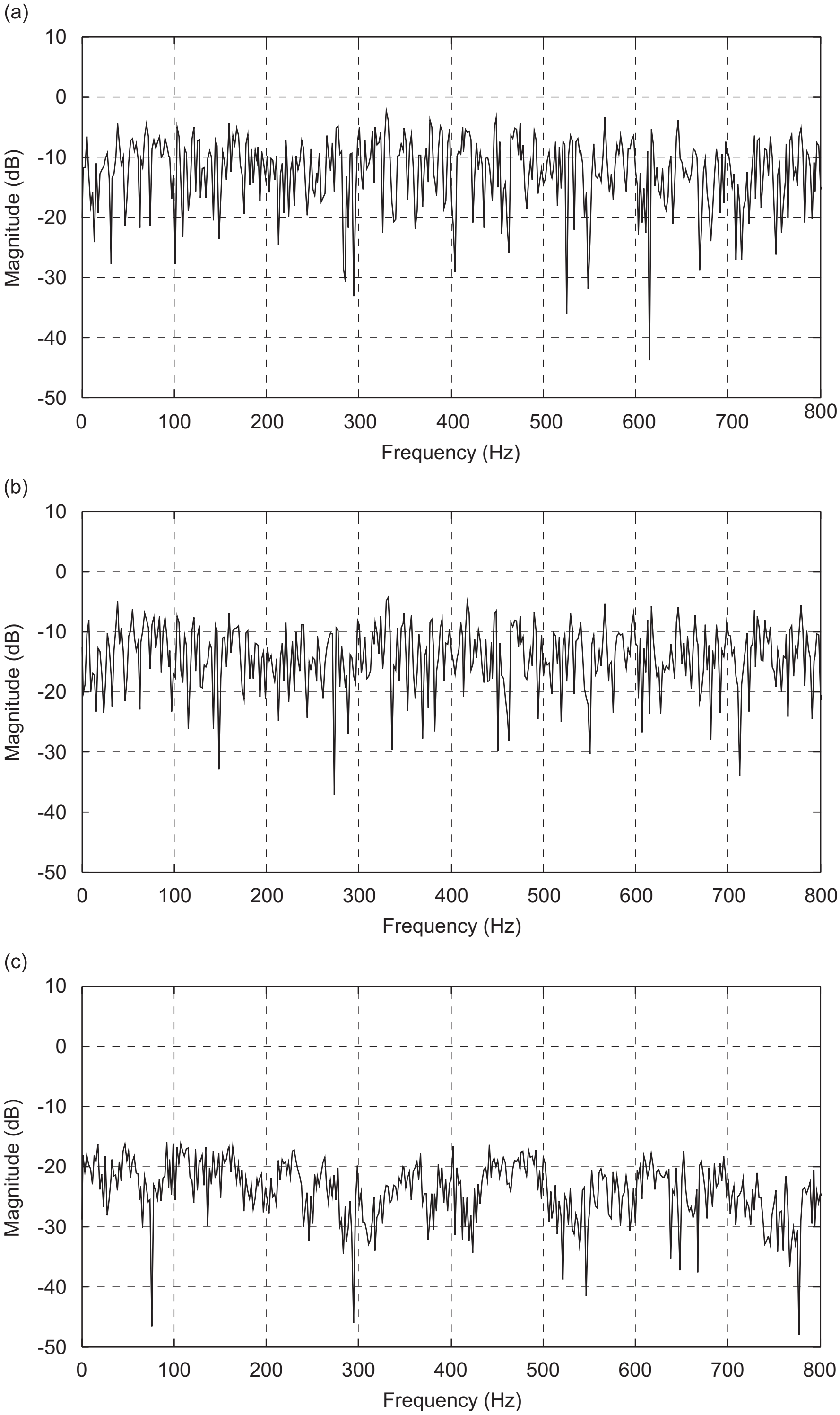

Fig. 5. ANC of broadband noise: (a) original broadband noise, (b) ANC with FXLMS, and (c) ANC with NFXLMS.

[16]. The complexity of control problem should also be taken into consideration when deciding the number of input nodes and hidden nodes. The proposed neural ANC filter is based on 4 input nodes, 6 hidden nodes, and 1 output node neural network with NFXLMS algorithm. One uses only 4 input nodes to save the computing

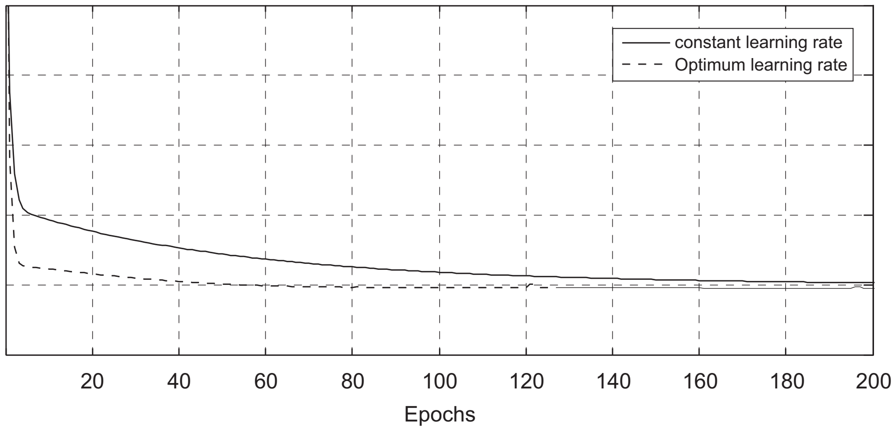

Fig. 6. Performance of the optimal (dotted) and constant learning rates (solid) for NFXLMS algorithm.

effort and uses almost twice the number of input nodes to be the number of hidden nodes because the ANC system is complex. The proposed NFXLMS also helps to enhance the system performance. Experiments show that the proposed 4–6–1 neural ANC filter with NFXLMS algorithm can outperform the conventional 32nd-order FXLMS ANC system.

4. Conclusions

One derives the NFXLMS algorithm from neural network with error backpropagation algorithm. The nonlinear processing ability of the neural network improves the noise cancellation performance in an ANC system. Choosing $f_h(\mathrm{net}_j) = \mathrm{net}_j$ and $f_o(\mathrm{net}_o) = \mathrm{net}_o$ as the activation functions of the neural filter helps to avoid the premature saturation of backpropagation algorithm. One also designs the optimum learning rate to accelerate the convergence. Computer simulations have been carried out to demonstrate the performance of the NFXLMS as a useful method for nonlinear ANC system. Compared to FXLMS, it is obvious that the NFXLMS algorithm shows the enhancement in nonlinear broadband noise cancellation. The proposed algorithm is also versatile and can be used in other applications.

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