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# Evaluating the Performance of MLP Neural Network and GRNN in Active Cancellation of Sound Noise

M. Salmasi, H. Mahdavi-Nasab, and H. Pourghassem

**Abstract —** *Active noise control (ANC) is based on the destructive interference between the primary noise and generated noise from the secondary source. An antinoise signal with equal amplitude and opposite phase is generated and combined with the primary noise. In this paper, the performance of two kinds of feedforward neural networks in active noise cancellation is evaluated. For this reason, multilayer perceptron (MLP) and generalized regression neural networks (GRNN) are designed and trained with acoustic noise signals. After training, performance of these networks in noise attenuation is investigated and compared. In order to compare the two networks, training and test samples are similar. Sound noise signals are selected from SPIB database. The results of simulation show the ability of MLP network and GRNN in active cancellation of sound noise. As it is seen, multilayer perceptron network has better performance in noise attenuation than the generalized regression neural network.*

**Key Words — Active Noise Control (ANC), Feedback ANC system, Generalized Regression Neural Network, Multilayer Perceptron Neural Network.**

## I. INTRODUCTION

With the growth of technology and industrial equipments such as fans and transformers, acoustic noise problems are more and more evident. Control of acoustic noise is based on two approaches: Passive and active methods. Passive methods such as barriers, silencers and isolation are large, costly and ineffective at low frequencies. These problems were caused to use active noise cancellation instead of passive techniques. Active noise control (ANC) cancels the primary noise based on the principle of superposition. An antinoise signal with the same amplitude and opposite phase is produced and combined with the primary noise [1], [2]. Physical concept of active noise control is shown in Fig. 1.

Active noise control has several applications include attenuation of unwanted acoustic noise in the following end equipment [3].

1) Transportation: Such as helicopters, airplanes, ships, motorcycles, and so on.
2) Appliances: Such as air-conditioning ducts, refrigerators, air conditioners, and so on.
3) Industrial: Such as blowers, transformers, compressors, fans, pumps, headphones, and so on.

New applications of ANC have been introduced in [4].

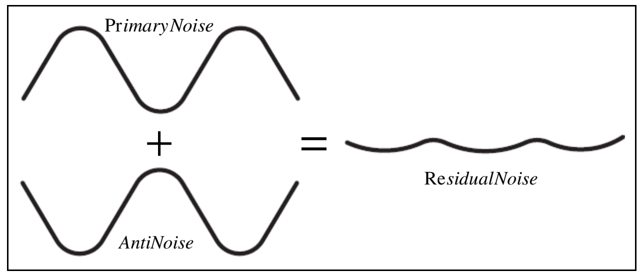


**Fig. 1. Noise, Antinoise and Residual Noise of an ANC system**

Paul Lueg in 1936 published a patent and presented the new idea of ANC utilizing a microphone and an electronically driven loudspeaker. Lack of technology delayed implementation of active noise cancellation systems. The digital designs appeared in about 1975 [5], [6]. For years adaptive filters and filtered-x LMS algorithm were the best choice for ANC systems. But it was just about simple models of channels and loudspeakers. When the sound passes through some complicated structures and acoustic paths, nonlinearity gets more important role. Another source of nonlinearity is loudspeaker. When the amplitude increases some nonlinear effects happen to output sound. One of the best-known structures for dealing with nonlinear behaviors is neural network. The neural networks have nonlinear properties and these properties help them in nonlinear processes [7], [8]. In [9], it was shown that neural networks have better performance than adaptive filters in nonlinear conditions. Different neural networks such as MLP, RBF and recurrent networks have been used for active noise control [10]-[12].

There are two types of ANC systems. The first one is feedforward control and the second one is feedback control. In feedforward control systems, a reference noise signal is sensed. Structures for feedforward ANC systems are classified into broadband feedforward control with a reference sensor and narrow-band feedforward control with a reference sensor that is not influenced by the control field (e.g. tachometer). In feedback ANC systems the reference signal is unknown and the main idea is to regenerate the reference signal [3]. Figs. 2 and 3 show the feedforward and feedback ANC systems, respectively.

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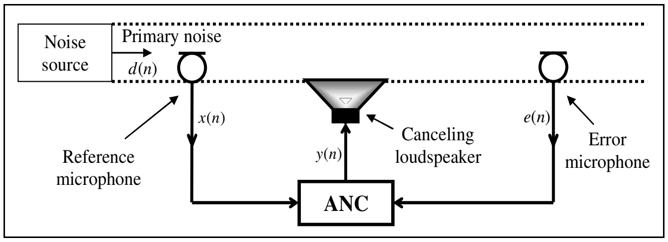


**Fig. 2. Single-channel feedforward ANC system**

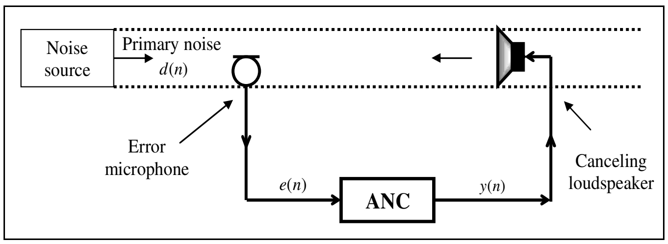


**Fig. 3. Single-channel feedback ANC system**

In this paper, multilayer perceptron and generalized regression neural networks are used for active noise control. These networks are designed and trained for canceling acoustic noise. The main idea is to compare the performance of trained networks in noise attenuation of unwanted acoustic noise. Acoustic noise signals are selected from SPIB database. The ability of these networks in active cancellation of acoustic noise is shown in simulation results. A part of this paper is appeared in [13]. Feedback ANC system and its block diagram is discussed in section 2. Section 3 presents the structure of designed neural networks and section 4 shows simulation results. Finally, conclusions are drawn in section 5.

## II. Feedback Active Noise Control System

A feedback ANC approach will be taken in this paper. In the feedback ANC system shown in Fig. 3, the primary noise signal d(n) is not available. Therefore, the main idea of an adaptive feedback ANC system is to regenerate the reference signal d(n) from the error signal [3]. The basic block diagram of the feedback ANC system is shown in Fig. 4.

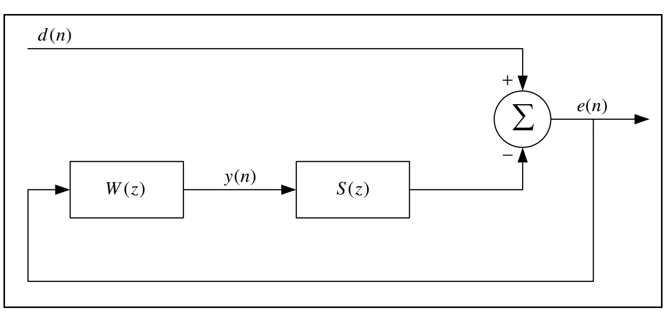


**Fig. 4. Basic block diagram of the feedback ANC system**

Where d(n) is the primary noise, y(n) is the antinoise signal, e(n) is the residual noise and W(z) is the transfer function of the controller. S(z) is the transfer function of the secondary path from canceling loudspeaker to the error microphone. From Fig. 4, we can see that the primary noise can be expressed in the z-domain as,

$$D(z)=E(z)+S(z)Y(z) \tag{1}$$

The secondary path transfer function S(z) can be estimated as $\hat{S}(z)$. Thus we can estimate the primary noise d(n) and use this as a synthesized reference signal x(n) as,

$$X(z)\equiv\hat{D}(z)=E(z)+\hat{S}(z)Y(z) \tag{2}$$

Fig. 5 shows a complete block diagram of the feedback ANC system.

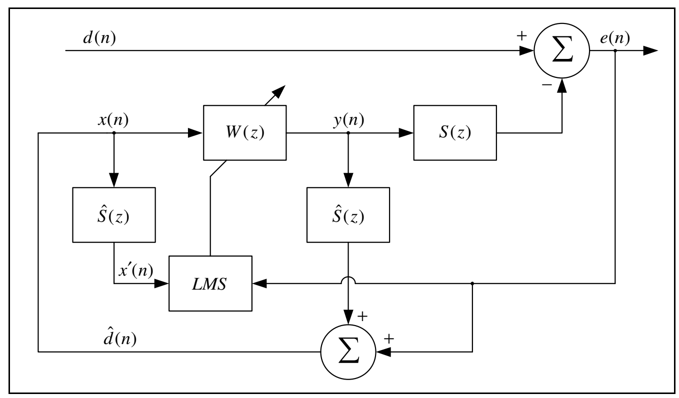


**Fig. 5. Complete block diagram of the feedback ANC system**

From Fig. 5, we can see that the reference signal x(n) and the secondary signal y(n) can be expressed as,

$$x(n)\equiv\hat{d}(n)=e(n)+\sum_{m=0}^{M-1}\hat{s}_m\, y(n-m) \tag{3}$$

$$y(n)=\sum_{l=0}^{L-1}w_l(n)\,x(n-l) \tag{4}$$

Where $\hat{s}(m)$, m = 0, 1, . . . , M-1 is the M$^{th}$ order FIR filter used to approximate the secondary path transfer function. $w_l$(n), l = 0, 1, . . . , L-1 are the coefficients of the L$^{th}$ order adaptive FIR filter W(z) at time n. These coefficients are updated by the FXLMS algorithm as,

$$w_l(n+1)=w_l(n)+\mu\, x'(n-l)\,e(l) \tag{5}$$

Where μ is the step size and $x'(n)$ is the filtered reference signal. From equations (1) and (2) it is concluded that x(n)=d(n) if $\hat{S}(z)=S(z)$. Assuming that this condition is satisfied, then the adaptive feedback ANC system can be transformed into the feedforward ANC system. If the LMS algorithm has slow convergence, i.e. the step size μ is small then the adaptive filter W(z) can be commuted with the secondary path transfer function S(z). Further, if we assume that the secondary path S(z) can be modeled as a pure delay i.e. $S(z)=z^{-\Delta}$ , then the feedback ANC system is equivalent to the standard adaptive predictor [3]. Block diagram of a standard adaptive predictor is shown in Fig. 6.

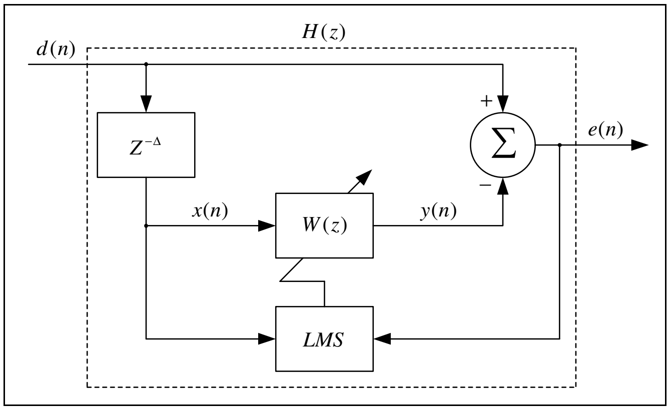


**Fig. 6. Block diagram of standard adaptive predictor**

So the feedback ANC system acts as an adaptive predictor of the primary noise to minimize the residual error noise. In Fig. 6, H(z) is the overall transfer function of the feedback ANC system from d(n) to e(n) and is given by,

$$H(z) = \frac{E(z)}{D(z)} = 1 - S(z)W(z) \tag{6}$$

## III. NEURAL NETWORKS ARCHITECTURE

In this paper, a neural network is used as a predictor of the primary noise. Fig. 7 shows final block diagram used in this research. In simulation procedures, the secondary path S(z) is assumed as a pure delay $S(z)=z^{-1}$ .

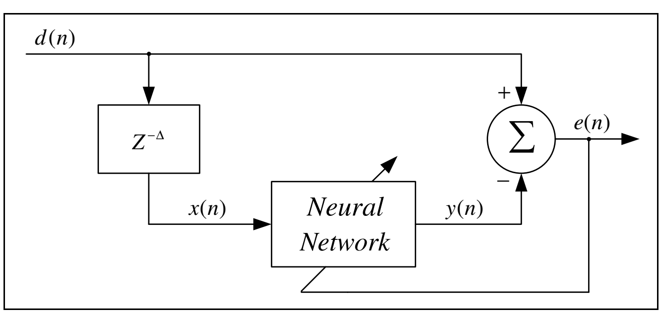


**Fig. 7. Block diagram of the predictor using neural network**

Neural network accepts N samples as its input and then using these N samples for predicting the (N+1)'th sample. The predicted sample is the output of the neural network and is used for feeding the antinoise speaker. Loudspeaker generates a sample with the same amplitude and 180 degrees difference in phase. Multilayer perceptron and generalized regression neural networks are used as a predictor.

Function approximation is one of the important applications of MLP neural networks. A two layer MLP network is designed and trained for ANC. For training the MLP network we use backpropagation algorithm. The first layer transfer function is sigmoid and the second layer is linear. The designed network has 20 inputs, 20 neurons in its hidden layer and 1 neuron in its output layer. Therefore, the MLP network has the structure of 20-20-1.

A generalized regression neural network is often used for function approximation. It is one of the type neural networks that can be used for prediction. It has a radial basis layer and a special linear layer. The GRNN has many advantages, but it suffers from one major disadvantage. It is slower to operate because it uses more computation than other kinds of networks to do its function approximation [14]. The designed GRNN network is a two layer network. It has 20 inputs and 1 neuron in its output layer. The first layer has as many neurons as there are input vectors.

The input to the networks is a tapped delay line (TDL). For training the networks, sound noise samples are fed to the inputs of networks. The target is the sample that comes after the present 20 samples. Therefore, the neural network is a predictor of d(n) from d(n-1), d(n-2), . . . , d(n-19), d(n-20).

## IV. SIMULATION RESULTS

Noise data from a Signal Processing Information Base (SPIB) are used for simulation procedures. SPIB database have been provided by the Rice University. SPIB database consists of acoustic noise from different environments such as tank noise, factory noise, airplane cockpit noise and car interior noise. In [15], by using SPIB database, noise attenuation level for different types of ANC systems are investigated. In [16], the noise of F16 cockpit and also the noise of destroyer operation room are canceled using MLP network and the noise attenuation of 20 dB is achieved.

In this paper, four types of acoustic noise signals are used. For this reason, tank noise, F16 cockpit noise, factory noise and Buccaneer jet noise are selected from SPIB database. These acoustic noise signals were recorded at a sampling rate of 19.98 kHz with 16 bit resolution. Noise samples are split into two parts, training sets (2000 samples) and testing sets (other samples). After training the networks with each noise, test procedure is done three times. Test samples consist of 7000 samples of noise. In test procedure, performance of the trained networks in noise attenuation is evaluated and compared. Noise attenuation is calculated from,

$$Noise\,Attenuation = 10 \times \log_{10} \frac{Input\,Noise\,Energy}{Remained\,Noise\,Energy} \quad (7)$$

First simulation is done with m109 tank noise. The m109 tank was moving at a speed of 30 km/h. MLP network and GRNN are trained with 2000 samples of tank noise. After training, test samples are fed to the network three times. In table I, the performance of the networks in noise attenuation is shown.

**TABLE I**
**PERFORMANCE OF THE TRAINED NETWORKS FOR M109 TANK NOISE**

| | Noise Attenuation (dB) | |
|---|---|---|
| | **MLP** | **GRNN** |
| **1st test** | 26.3619 | 22.7124 |
| **2nd test** | 27.2187 | 23.4505 |
| **3rd test** | 26.4712 | 22.673 |

Suppose that 3000 samples of tank noise are fed to the trained MLP network. Fig. 8 shows the noise signal of m109 tank. The neural network should predict new samples of noise. Antinoise signal generated with MLP neural network is shown in Fig. 9. As it is seen, noise and antinoise signals are vise versa. The addition of noise and antinoise is called residual noise. Fig. 10 shows the residual noise.

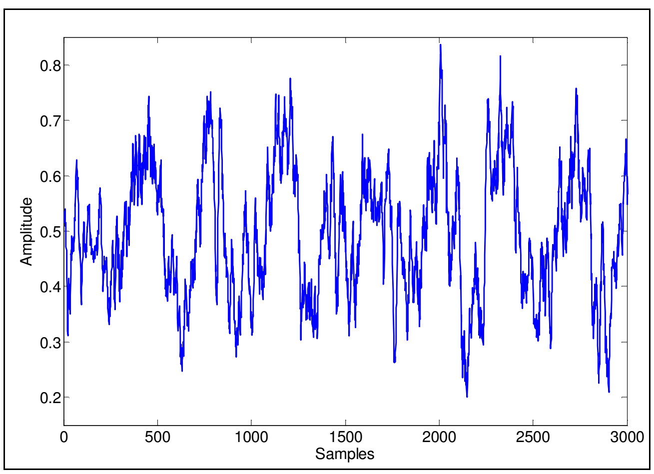


**Fig. 8. Noise signal of m109 tank**

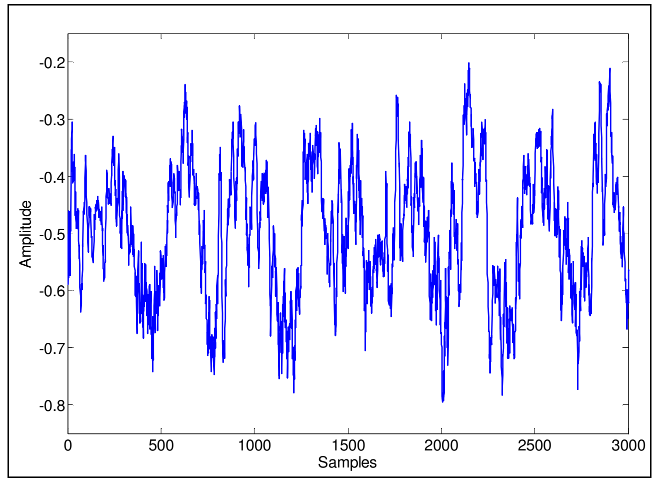


**Fig. 9. Antinoise signal generated with MLP neural network**

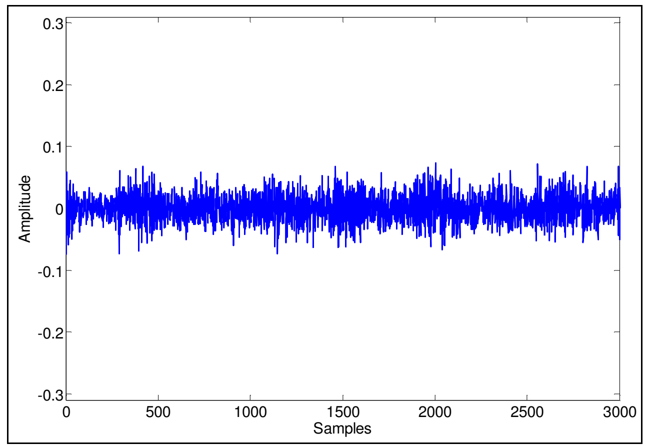


**Fig. 10. Residual noise**

Noise signal from a Buccaneer jet cockpit is used for second simulation. The Buccaneer jet was moving at a speed of 190 knots, and an altitude of 1000 feet with airbrakes out. The performance of the networks in noise attenuation of Buccaneer jet is shown in table II.

**TABLE II**
**PERFORMANCE OF THE TRAINED NETWORKS FOR BUCCANEER JET NOISE**

| | Noise Attenuation (dB) | |
|---|---|---|
| | **MLP** | **GRNN** |
| **1st test** | 18.677 | 16.4137 |
| **2nd test** | 18.7452 | 16.4845 |
| **3rd test** | 18.5528 | 16.151 |

Suppose that 3000 samples of Buccaneer jet noise are fed to the Trained MLP network. Power spectrum of the Buccaneer jet noise and residual noise are shown in Fig. 11. The dashed line represents the Buccaneer jet noise spectrum and the solid line denotes the residual noise spectrum. From these two spectra, it is concluded that the ANC system achieved good noise reduction from DC to 3 kHz.

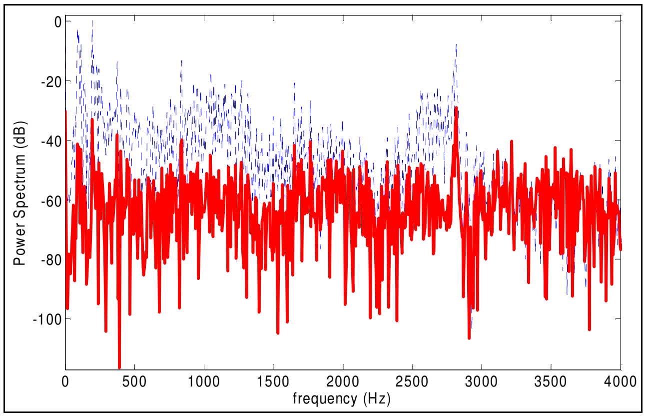


**Fig. 11. Buccaneer jet noise spectrum (dashed line) and residual noise spectrum (solid line)**

The performance of the networks in noise attenuation of factory and F16 cockpit are shown in tables III and IV, respectively. Noise signal from a factory was recorded near plate-cutting and electrical welding equipment. F16 cockpit noise was recorded at the co-pilot's seat in a two-seat F16, traveling at a speed of 500 knots, and an altitude of 300-600 feet.

**TABLE III**
**Performance of the trained networks for factory noise**

| | Noise Attenuation (dB) | |
|---|---|---|
| | **MLP** | **GRNN** |
| **1st test** | 22.5858 | 20.2212 |
| **2nd test** | 21.3968 | 19.4903 |
| **3rd test** | 23.1856 | 21.8067 |

**TABLE IV**
**Performance of the trained networks for F16 cockpit noise**

| | Noise Attenuation (dB) | |
|---|---|---|
| | **MLP** | **GRNN** |
| **1st test** | 24.7356 | 20.429 |
| **2nd test** | 23.4638 | 19.2557 |
| **3rd test** | 24.8225 | 20.5921 |

From tables I-IV it is concluded that MLP network has better performance in noise attenuation than generalized regression neural network. Fig. 12 shows power spectrum of the factory noise (3000 samples) and residual noise.

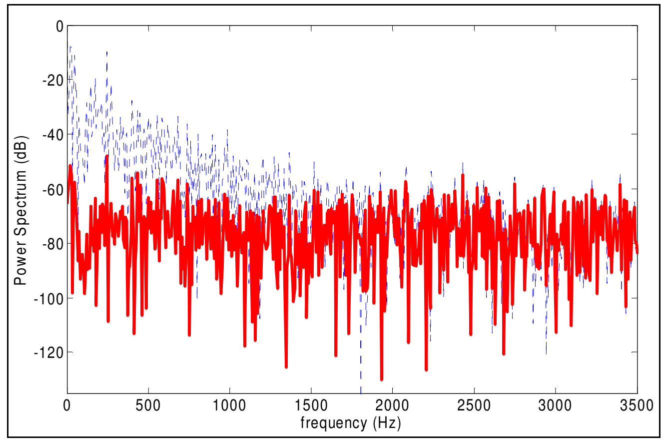


**Fig. 12. Factory noise spectrum (dashed line) and residual noise spectrum (solid line)**

From these spectra, it is seen that the ANC system achieved good noise reduction from DC to 2 kHz.

## V. Conclusion

In this paper, active cancellation of acoustic noise was done with multilayer perceptron and generalized regression neural networks. These networks were designed and trained with acoustic noise samples from different environments. After training, performance of the networks in noise reduction was compared. The results of simulation demonstrated that both of the networks have good performance in noise attenuation. Power spectrum of the main noise and residual noise showed that neural networks achieved good noise reduction in low frequencies. It was seen that MLP network can cancel the noise more efficiently than GRNN.

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