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Comparison of Feed-Forward and Recurrent Neural Networks in Active Cancellation of Sound Noise

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Abstract— **Passive techniques such as barriers, silencers and isolation are bulky, costly and ineffective at low frequencies. Active cancellation of noise was presented because of these problems. In this paper, we want to investigate the uses of neural networks in active noise control (ANC). Feed-forward and recurrent neural networks are compared for active cancellation of sound noise. In order to compare the two networks the number of layers and neurons are equal in both of the networks. Moreover, training and test samples are similar for networks. The noise signals that are used for training the networks are selected from SPIB database. The results of simulation show the ability of these networks in noise cancellation. As it is seen, recurrent neural network has better performance in noise attenuation than the feed-forward neural network.**

Keywords-Active Noise Control (ANC); Feed-forward Neural Network; Recurrent Neural Network

I. INTRODUCTION

Urbanization and progression of industrial factories is an important reason for increasing acoustic problems. Passive sound absorbers and isolation are large, expensive and ineffective at low frequencies. These problems and other problems were caused to use active cancellation of noise instead of passive sound methods. In 1936, Paul Lueg published a patent and presented the new idea of active noise cancellation. Active noise cancellation (ANC) is based on destructive interference between the noise source waves and a controlled secondary source. Physical concept of active noise control is shown in figure 1. Lack of technology delayed implementation of active noise cancellation systems. The digital designs appeared in about 1975 [1, 2].

Some of the applications of active noise control are fan noise reduction, acoustic noise cancellation in MR imaging, engine noise cancellation, reduction of car interior noise and control of aircraft cabin noise [2, 3]. In [4] new applications of ANC have been introduced.

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. This again results in harder processes for getting a good ANC [5]. 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 [6, 7]. Different neural networks such as MLP, RBF and recurrent have been used for active noise control [8, 9, 10].

In this paper, different neural networks are used for active noise control. Feed-forward and recurrent neural network are designed for canceling sound noise. The main idea is to compare the performance of these networks in noise reduction of unwanted noise. Noise signals are selected from SPIB database. The simulation results show that recurrent neural networks can cancel the noise more efficiently than feed-forward neural networks.

Section II presents active noise control system that we used in this paper. In section III the structure of neural networks are shown. Section IV shows the Simulation results and conclusions are given in section V.

II. TYPES OF ANC SYSTEMS

There are two types of ANC systems. The first one is called feed-forward control and the second one is feedback control. In feed-forward control systems, a reference noise signal is sensed, while in feedback systems this reference signal is unknown. Structures for feed-forward ANC systems are classified into broadband feed-forward control with a reference sensor and narrow-band feed-forward control with a reference sensor that is not influenced by the control field (e.g. tachometer) [3]. Figure 2 and figure 3 show the feed-forward and feedback ANC systems, respectively.

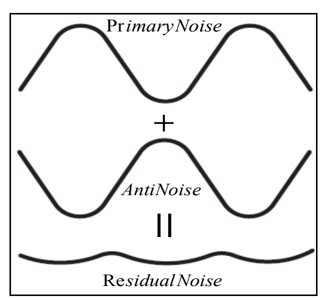

Figure 1: Noise, Antinoise and Residual Noise of an ANC system

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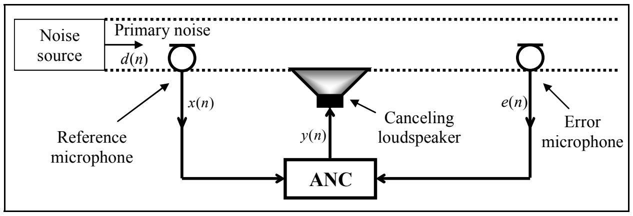

Figure 2. Single-Channel feed-forward ANC system

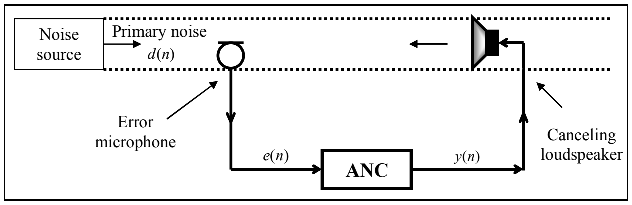

Figure 3: Single-Channel feedback ANC system

A feedback ANC approach will be taken in this research. In the feedback ANC system shown in figure 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.

From figure 3, we can see that the primary noise can be expressed in the z-domain as $D(z)=E(z)+S(z)Y(z)$, where E(z) is the residual error signal, Y(z) is the output of the adaptive filter and S(z) is the secondary path transfer function. The secondary path transfer function S(z) can also 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 $X(z)\equiv\hat{D}(z)=E(z)+\hat{S}(z)Y(z)$.

A complete block diagram of the feedback ANC system is shown in Figure 4. From figure 4, we can see that the reference signal x(n) and the secondary signal y(n) can be expressed as,

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

$$y(n)=\sum_{l=0}^{L-1} w_l(n)\, x(n-l) \qquad (2)$$

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,

$$w_l(n+1)=w_l(n)+\mu\, x'(n-l)\, e(l) \qquad (3)$$

Where μ is the step size and $x'(n)$ is the filtered reference signal.

We can see 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 feed-forward 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 as shown in figure 5.

So the feedback ANC system acts as an adaptive predictor of the primary noise to minimize the residual error noise. In this research, we use a neural network instead of adaptive filters that will be described in section III. Figure 6 shows the final block diagram that we used in this research. In simulation procedures, the secondary path S(z) is assumed as a pure delay $S(z)=z^{-1}$.

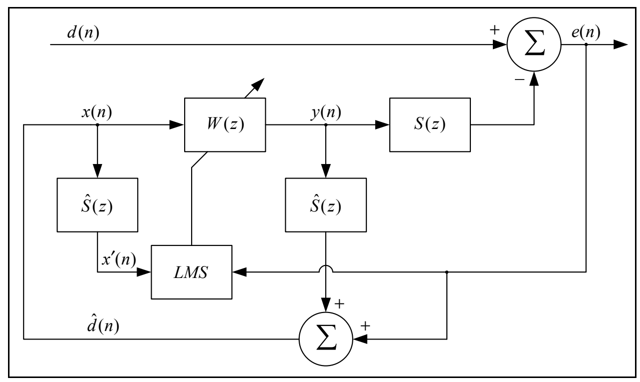

Figure 4: complete block diagram of the feedback ANC system

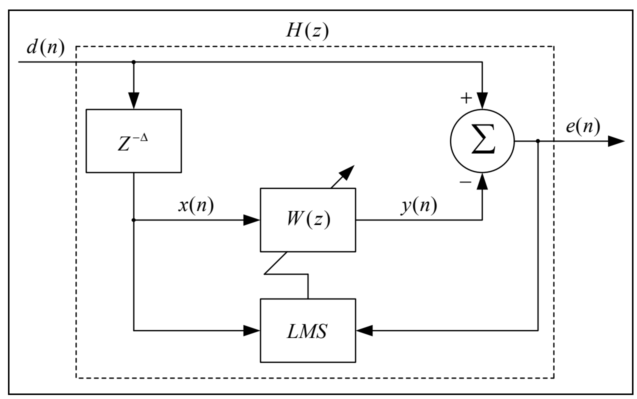

Figure 5: Block diagram of standard adaptive predictor

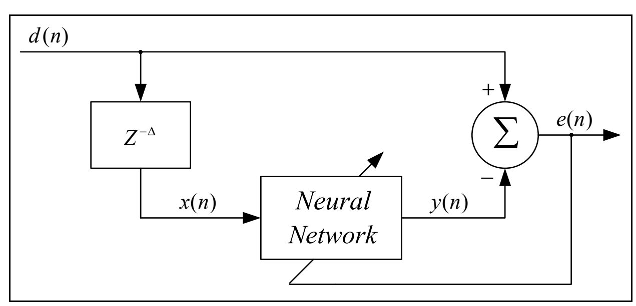

Figure 6: Block diagram of predictor using neural network

III. STRUCTURE OF NEURAL NETWORKS

As it was seen, we use a neural network as a predictor of the primary noise. Neural networks 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 anti-noise speaker. Loudspeaker generates a sample with the same amplitude and 180 degrees difference in phase. Feed-forward and recurrent neural network are used as a predictor in sequence.

Feed-forward neural networks are one of the best candidates for function estimation and other usual processing tasks. Back-propagation algorithm is well suited to these networks [2, 11]. A tow layer feed-forward neural network is designed. The structure that is used for this neural network has been shown in figure 7.

Recurrent neural networks are useful in temporal systems. We use Elman network as a recurrent neural network. The Elman network commonly is a two-layer back-propagation network with a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman networks to detect and generate time-varying patterns. The delay in the feedback connection stores values from the previous time step. These values can be used in the current time step. The structure that is used for Elman network has been shown in figure 8.

As it is seen in figure 7 and figure 8, the first layer transfer function is sigmoid and the second layer transfer function is linear. The input to the networks is a Tapped Delay Line (TDL). Both of the designed neural networks have 20 inputs, 20 neurons in their hidden layer and 1 neuron in their output layer. So the neural networks have the structure of 20-20-1.

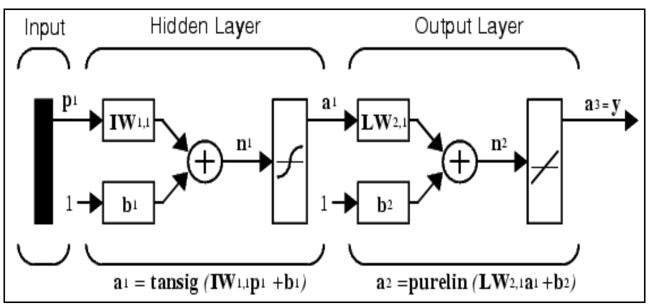

Figure 7: Structure of the feed-forward neural network

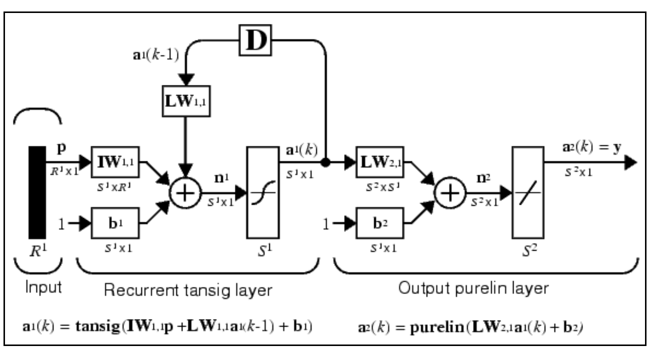

Figure 8: Structure of the Elman neural network

For training the networks, sound noise samples are fed to inputs of the networks. The target is the sample that comes after the present 20 samples. So 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

For simulations, noise data from a Signal Processing Information Base (SPIB) are used. SPIB database have been provided by the Rice University. In [11], the noise of F16 and also the noise of destroyer engine room noise are canceled using MLP neural network and the noise reduction of 20 dB is achieved. In [12], by using SPIB database, noise attenuation level for different types of ANC systems are compared.

We use four types of SPIB database which include a F16 cockpit noise, Destroyer engine room noise, Vehicle interior noise (Volvo) and Military vehicle noise (Leopard). The noise was recorded at a sampling rate of 19.98 kHz with 16 bit resolution. The noise samples are split into two parts, training sets (2,000 samples) and Testing sets (other samples). After training the networks with each noise, testing procedure is done three times.

In first simulation, F16 cockpit noise is selected from the database. The 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. Feed-forward and recurrent neural networks are trained with F16 noise signal. After training, test samples are fed to the network three times. 10,000 samples are used for test samples. In table I, the performance of the networks in noise attenuation has been shown. Noise attenuation is calculated from,

$$Noise\ Attenuation = 10 \times \log_{10} \frac{Input\ Noise\ Energy}{Remained\ Noise\ Energy} \qquad (4)$$

Suppose that 500 samples of F16 noise are fed to the trained Elman network. The neural network should predict new samples of noise and generate anti-noise signal to cancel the noise. Figure 9 shows the noise signal of F16. Anti-noise signal generated with Elman neural network has been shown in figure 10. The addition of noise and anti-noise which is called residual noise has been shown in figure 11.

TABLE I. PERFORMANCE OF THE NETWORKS FOR F16 NOISE SIGNAL

	Noise Attenuation (dB)	
	Feed-Forward Neural Network	***Recurrent Neural Network***
1st test	23.7335	25.1345
2nd test	24.75	25.5037
3rd test	24.478	25.3954

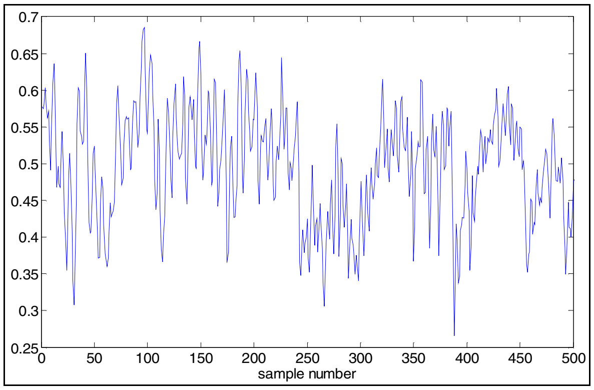

Figure 9: F16 noise signal

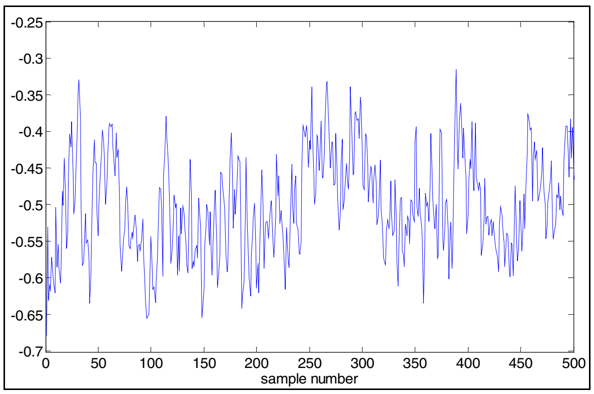

Figure 10: Anti-noise signal generated with Elman neural network

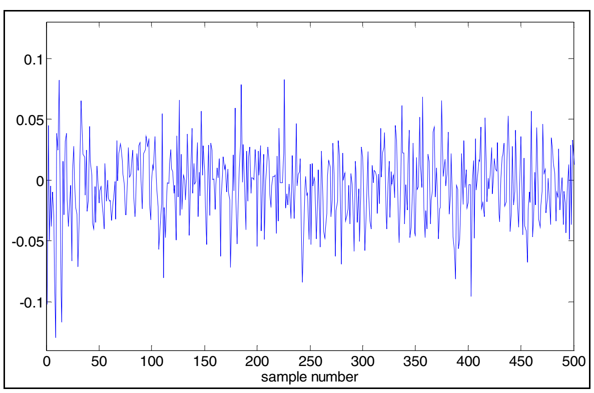

Figure 11: Residual noise

Second simulation is done with destroyer engine room noise. In table II the performance of the networks in noise attenuation of destroyer engine room noise has been shown. Table III and table IV show the performance of the networks in noise attenuation of Volvo noise and Leopard noise, respectively. Noise recording of Volvo was made at 120 km/h, in 4th gear, on an asphalt road, in rainy conditions. The Leopard vehicle was moving at a speed of 70 km/h.

From table I-IV it is concluded that both of the feed-forward and recurrent neural networks have the ability of canceling noise. As it is seen, recurrent neural network has better performance in noise attenuation than feed-forward neural networks.

TABLE II. PERFORMANCE OF THE NETWORKS FOR DESTROYER ENGINE ROOM NOISE SIGNAL

	Noise Attenuation (dB)	
	Feed-Forward Neural Network	***Recurrent Neural Network***
1st test	22.9461	23.9076
2nd test	23.5132	24.0004
3rd test	22.9781	23.5339

TABLE III. PERFORMANCE OF THE NETWORKS FOR VOLVO NOISE SIGNAL

	Noise Attenuation (dB)	
	Feed-Forward Neural Network	***Recurrent Neural Network***
1st test	47.1487	49.5744
2nd test	45.2066	48.2081
3rd test	47.8032	50.6561

TABLE IV. PERFORMANCE OF THE NETWORKS FOR LEOPARD NOISE

	Noise Attenuation (dB)	
	Feed-Forward Neural Network	***Recurrent Neural Network***
1st test	40.8741	42.79
2nd test	41.2916	43.2439
3rd test	40.4198	42.6719

V. CONCLUSIONS

In this paper, active cancellation of sound noise was done with feed-forward and recurrent neural networks. Both of the networks were trained with noise samples from SPIB database. After training, the performance of the networks in noise reduction was compared. The ability of feed-forward and recurrent neural networks in noise cancellation was shown in simulation results. It was seen that recurrent neural networks are more effective in canceling sound noise than feed-forward neural networks.

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