Functional Link Artificial Neural Network for Active Control of Nonlinear Noise Processes

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***Abstract* – There are several situations where the conventional ANC using FXLMS algorithm does not perform satisfactory. One such condition is referred as the nonlinear effect in ANC. This paper proposes an efficient novel ANC structure based on functional link artificial neural network, which outperforms the FXLMS algorithm. This has been demonstrated through computer simulation.**

***Index Terms* – ANC, nonlinear effect, functional link artificial neural network (FLANN).**

I. INTRODUCTION

Due to the exponential increase of noise pollution and inactiveness of the passive techniques for noise mitigation, particularly for low frequency noise, there is an increasing demand of research and developmental work on active noise control (ANC) technique [1]-[3]. Based upon the technique of destructive interference the ANC is efficient enough for noise cancellation for linear noise processes [1]-[3]. Filtered –X LMS algorithm is being used for the linear adaptive active noise controller to produce secondary noise to cancel the primary noise.

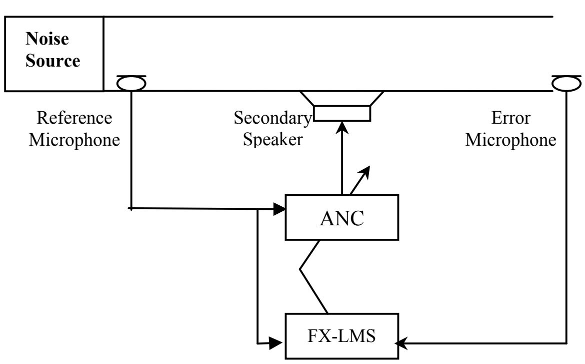

Fig. 1 - Block diagram of single channel ANC

A simple feedforward control system [1]-[3] for a long, narrow duct and its block diagram is illustrated in Fig. 1. A reference signal is sensed by an input microphone close to the noise source before it passes the canceling loudspeaker. The noise canceller uses the reference input signal to generate a signal of equal amplitude but 180° out of phase. This antinoise signal is used to drive the loudspeaker to produce a canceling sound that attenuates the primary acoustic noise in the duct. The basic principle of the broadband feedforward approach is that the propagation time delay between the upstream noise sensor (input microphone) and the active control source (speaker) offers the opportunity to electrically reintroduce the noise at a position in the field where it will cause cancellation. The spacing between the microphone and the loudspeaker must satisfy the principles of causality and high coherence, meaning that the reference must be measured early enough so that the antinoise signal can be generated by the time the noise signal reaches the speaker. The error microphone measures the residual error signal, which is used to adapt the filter coefficients to minimize this error. The use of a downstream error signal to adjust the adaptive filter coefficients does not constitute feedback, because the error signal is not compared to the reference input. Actual implementations require additional considerations to handle acoustic effects in the duct.

The above system is assumed to be a linear system and the standard FXLMS algorithm is effectively used with less computational complexity. However, in some situation the [4]-[6], the linear controller fails to achieve the optimum performance. These are:

1. The reference noise sensed by a reference microphone is a nonlinear and predictable noise process (chaotic), while the secondary path transfer function of an ANC system has nonminimum phase.

2. The primary path exhibits nonlinear behavior.

Section II deals with a mathematical analysis of FLANN. Computer simulation study of the proposed model is presented in Section III and its performance is compared with that obtained from the conventional FXLMS based linear controller. The concluding remarks have been made in Section IV.

II. FUNCTIONAL LINK ANN (FLANN)

An artificial neural network (ANN) can approximate a continuous multivariable function $f(x)$. Let the approximating function be represented as $f_W(x)$. In the FLANN, a set of basis functions Φ and a fixed number of weight parameters W are used to represent the $f_W(x)$. With a suitable set of basis functions, the problem is then to find the weight parameters W that provides the best possible approximation of f on the set of input-output examples. The use of FLANN for the purpose of multidimentional function approximation has been discussed in [9]. The structure of a FLANN is shown in Fig. 2.

A. Structure of the FLANN

The FLANN consists of N basis functions $\{\phi_1, \phi_2, \ldots, \phi_N\} \in B_N$ with the following input-output relationship for jth output

$$\hat{y} = \rho(S_j); S_j = \sum w_{ji}\phi_i(X) \tag{1}$$

where $X \in A \subset R^n$, i.e., $X = [x_1 x_2 \ldots x_n]^T$ is the input pattern vector, $\hat{y} \in R^m$, i.e. $\hat{y} = [\hat{y}_1 \hat{y}_2 \ldots \hat{y}_m]^T$ is the output vector and $w_j = [w_{j1} w_{j2} \ldots w_{jN}]$ is the weight vector associated with the jth output of the FLANN. The nonlinear function $\rho(.) = \tanh(.)$.

Consider the m dimensional output vector, (1) can be written as

$$S = W\Phi \tag{2}$$

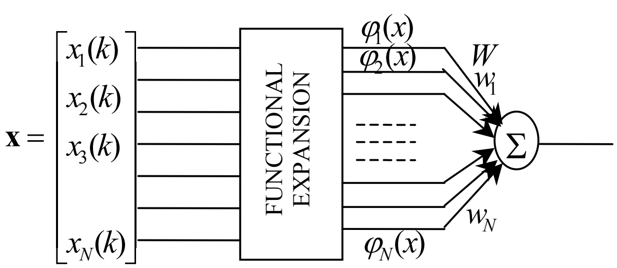

Fig. 2. The structure of a FLANN

where W is a $(m \times N)$ weight matrix of the FLANN given by $W = [w_1 w_2 \ldots w_m]^T$, $\phi = [\phi_1(X)\phi_2(X)\ldots\phi_N(X)]^T$ is the basis function vector, and $S = [S_1 S_2 \ldots S_N]^T$ is a matrix of linear outputs of the FLANN. The m dimensional output vector $\hat{y}$ may be given by

$$\hat{y} = \rho(S) = f_w(X) \tag{3}$$

Using the BP algorithm [9] for a single layer, the update rule for all the weights of the FLANN is given by

$$W(k+1) = W(k) + \mu\delta(k)\phi(X_k) \tag{4}$$

where $W(k) = [w_1(k) w_2(k) \ldots w_m(k)]^T$ is the $m \times N$ dimensional weight matrix of the FLANN at the kth time instant, $\delta(k) = [\delta_1, \delta_2, \ldots, \delta_m(k)]^T$, and $\delta_j(k) = (1 - \hat{y}_j(k)^2)e_j(k)$.

Suitable orthogonal polynomials for functional expansion, such as Legendre, Chebyshev and trigonometric polynomials are commonly used. In this paper we have used trigonometric functional expansion. The trigonometric polynomial basis functions given by

$$\{1, \cos(\pi u), \sin(\pi u), \cos(2\pi u), \sin(2\pi u), \ldots, \cos(N\pi u), \sin(N\pi u)\}$$

provides a compact representation of the function in the mean square sense.

III. COMPUTER SIMULATIONS

To show the effectiveness and robustness of the proposed algorithm computer simulations are conducted for various nonlinear situations in practical ANC system. In the simulation the secondary path transfer function $S(z)$ and its estimate $\hat{S}(z)$ are taken to be equal. For simulation studies one nonminimum phase transfer function and one minimum phase transfer function are taken whose pole zero plot are shown in Fig. 3. It is shown in Fig. 3 that for the nonminimum phase transfer function one zero is out side the unit circle where as for minimum phase transfer function the all are inside the unit circle.

Experiment I:

Here the primary noise signal is chosen to be a logistic chaotic type [7]. For simulation the noise is generated using

$$x(n+1) = \lambda(n)(1 - x(n)) \tag{5}$$

where λ =4 and $x(0)$ =0.9 are selected. This nonlinear noise process is then normalized to have unit signal power. The primary path transfer function is chosen to be

$$P(z) = z^{-5} - 0.3z^{-6} + 0.2z^{-7} \quad (6)$$

The secondary path transfer function is chosen to be the nonminimum phase as shown in Fig. 3. (a). Fig. 4. Shows the normalized mean square errors (NMSE) achieved by each ANC controller versus the number of iterations. From the plot it is apparent that the significant improvement of the performance in terms of NMSE is obtained by using FLANN based ANC.

Experiment II:

Here the primary noise signal and the primary path transfer function are chosen to be same as those of Experiment I. The secondary path transfer function is chosen to be the minimum phase as shown in Fig. 3. (b). Fig. 5. Shows the normalized mean square errors (NMSE) achieved by each ANC controller versus the number of iterations. From the plot it is apparent that there is no significant improvement of the performance in terms of NMSE obtained by using FLANN based ANC.

Experiment III:

Here the nonlinear primary path is taken for simulation. The primary noise at the canceling point is generated based on the following third-order polynomial model given in [7],

$$d(n) = t(n-2) + 0.08t^2(n-2) - 0.04t^3(n-1) \quad (7)$$

where $t(n) = x(n) * f(n)$ (8)

with $F(z) = z^{-3} - 0.3z^{-4} + 0.2z^{-5}$ (9)

The reference signal $x(n)$ is a sinusoidal wave of 500 Hz sampled at the rate of 8000 samples/s added with a Gaussian measurement noise of –40dB SNR. The secondary path transfer function is chosen to be the minimum phase as shown in Fig. 3. (b). Fig. 6 depicts the comparative plot of NMSEs for standard FXLMS and FLANN based ANC. From the figure it is found that the FLANN based ANC outperforms the standard FXLMS based ANC.

Experiment IV:

In this case the nonlinear primary path is also taken for simulation study. The primary noise at the canceling point is generated with the same equations given in Experiment III. The secondary path transfer function is chosen to be the nonminimum phase as shown in Fig. 3. (a). Fig. 7 depicts the comparative plot of NMSEs for standard FXLMS and FLANN based ANC. It is found from the figure that the FLANN based ANC outperforms the standard FXLMS based ANC for nonminimum secondary path.

IV. CONCLUSIONS

In this paper a functional link artificial neural network (FLANN) based ANC structure is developed for active mitigation of nonlinear noise processes. Simulation results depicts that the proposed FLANN based ANC outperforms the conventional FXLMS based ANC under two situations: 1) the reference noise is a nonlinear and predictable noise process, while the secondary path estimate is of nonminimum phase; 2) the primary path exhibits nonlinear behavior.

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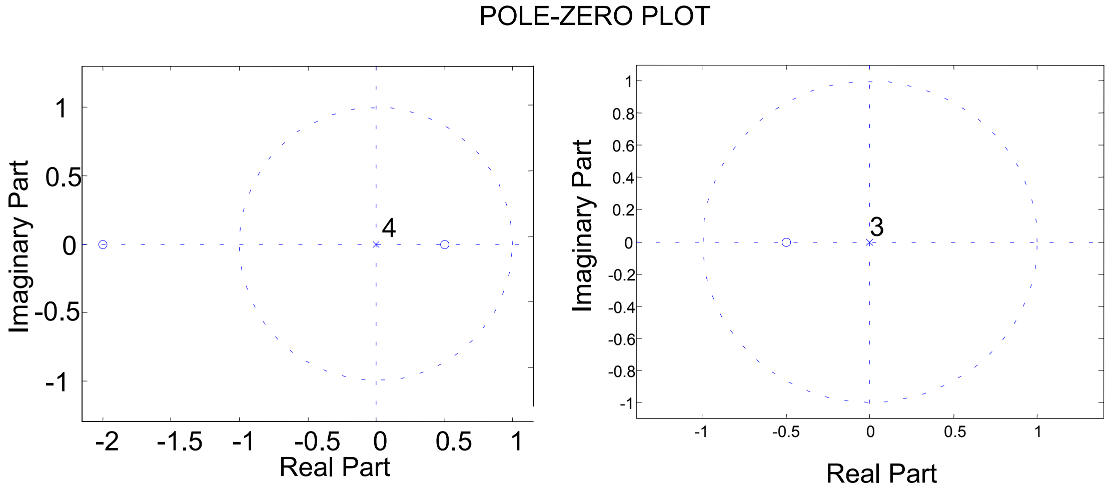

(a) (b)

Fig. 3 (a) Nonminimum phase (b) Minimum phase

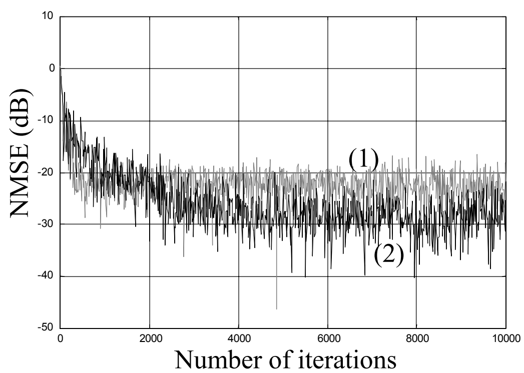

Fig. 4. Performance Comparison using secondary path estimate nonminimum phase (1) … Linear standard FXLMS algorithm with $\mu=2\times10^{-3}$ (2) FLANN with 20^{th} order functional expansion of a 11^{th} tap system having $\mu=1\times10^{-3}$.

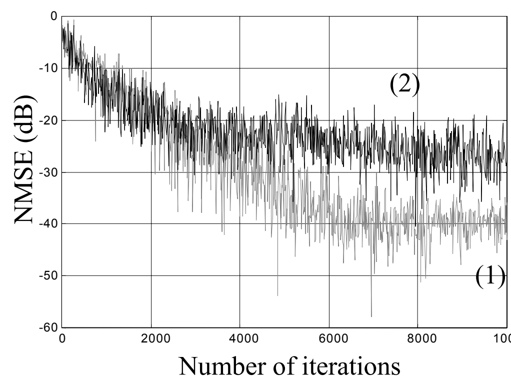

Fig.5. Performance Comparison using secondary path estimate minimum phase (1) … Linear standard FXLMS algorithm with $\mu=2\times10^{-3}$ (2) FLANN with 20^{th} order functional expansion of a 11^{th} tap system having $\mu=1\times10^{-3}$.

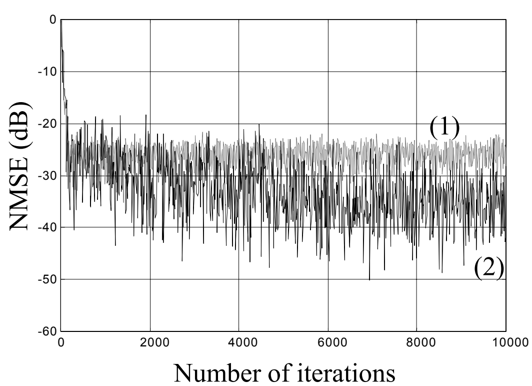

Fig. 6. Performance Comparison using secondary path estimate minimum phase (1) … Linear standard FXLMS algorithm with $\mu=2\times10^{-3}$ (2) FLANN with 20^{th} order functional expansion of a 11^{th} tap system having $\mu=1\times10^{-3}$.

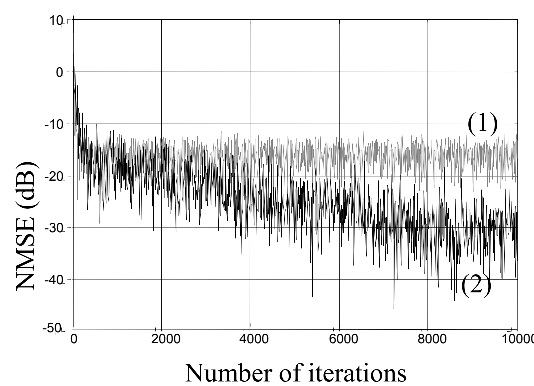

Fig. 7. Performance Comparison using secondary path estimate nonminimum phase (1) … Linear standard FXLMS algorithm with $\mu=2\times10^{-3}$ (2) FLANN with 20^{th} order functional expansion of a 11^{th} tap system having $\mu=1\times10^{-3}$.