Digital Control of Local Sound Fields in an Aircraft Passenger Compartment

J. V. Warner* and R. J. Bernhard†
Purdue University, West Lafayette, Indiana

Active noise control has been shown to be a promising solution for reducing noise levels in turboprop aircraft. The first part of this paper shows the performance of a broadband active noise control system based upon an off-line frequency domain model obtained from system response measurements. A laboratory test in an 18 passenger airplane fuselage resulted in 10–20 dB reduction of broadband deterministic noise over a substantial frequency range. However, the sensitivity of the system to environmental changes made clear the impracticality of using off-line modeling techniques. Thus the paper addresses the use of adaptive digital filtering techniques for active noise control in aircraft. Results are presented from a simulation study in which the Least Mean Square (LMS) and Recursive Least Mean Square (RLMS) gradient search techniques are used to model actual system response measurements. The LMS and RLMS algorithms were found to be equally capable of modeling the airplane system. However, for a dense harmonic sound field, the LMS estimator was superior, attenuating most harmonics by more than 30 dB, whereas the RLMS estimator reduced most harmonics by 20 dB.

Introduction

INCREASING fuel cost and competition among carriers has forced the transportation industry to improve the operating efficiency of its products. With propulsion systems redesigned for reduced fuel consumption and structural members made less massive to reduce weight, the passenger is likely to be subject to higher noise levels. This is potentially the case in the aircraft industry with the development of advanced turboprop engines. While advanced turboprop aircraft may offer 30% fuel savings over conventional turbofan engines in medium-sized, medium-range commercial aircraft, noise levels in some configurations have been predicted to reach higher than 150 dB at the fuselage.[1]

Using conventional passive techniques to adequately control such high noise levels will involve significant weight, thus, severely reducing potential fuel savings. Active noise control has been proposed as a potentially efficient method for attenuation of low frequency noise in aircraft. Analytical investigations by Bullmore, Nelson, and Elliott[2] and by Lester and Fuller[3] have predicted significant acoustic pressure reductions from active noise control systems in idealized cylindrical models of aircraft using frequency domain optimization techniques and multiple control sources. Zalas and Tichy[4] have demonstrated in actual aircraft that substantial reductions in interior noise levels at blade passage frequencies can be accomplished in local regions using a modified Widrow-Hoff algorithm and a single control source. Simplified demonstrations of active noise control in small cylinders have been presented by Abler and Silcox[5] using multiple acoustic control sources and by Jones and Fuller[6] using vibration control of the cylinder structure.

In this investigation, the digital implementation of active noise control at a local region is studied. The first part of this paper describes the results of an experimental feasibility study of local active noise control in an aircraft. An infinite impulse response (IIR) digital filter, derived from measured transfer functions, is used to produce a control signal that attenuates broadband noise at a passenger's head location inside an 18-passenger twin engine aircraft. During the course of this investigation, it was observed that the system performance changed considerably with changes in air temperature and humidity. The results made it obvious that any practical active noise controller must be able to adapt to environmental changes as well as to changes in actuators, sensors, and passenger cabin conditions. In addition, a relatively short IIR filter was effective, which motivated an investigation of adaptive IIR controller configurations.

To address the problem of slowly time-varying conditions in aircraft, the body of this paper investigates the use of gradient-based adaptive controllers to cancel noise at an airplane passenger location. A computer simulation, which uses measurements to replicate the system, was developed. Results for recursive and nonrecursive filter algorithms will be demonstrated. The effect of various parameters, such as filter type and length, on controller performance will be shown. Some of the expected difficulties involved in implementing adaptive digital active noise control systems will also be discussed.

Nonadaptive Control Results

Figure 1 shows a typical active sound control system for cancellation at a single point in space. Given some unwanted noise source N, a control source S, and a detector sensor D, a frequency response, H, is desired such that sound cancella-

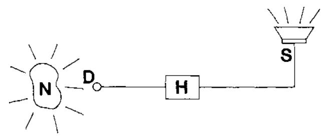

Fig. 1 Typical active sound control system for cancellation at a point in space.

Received Oct. 25, 1988; revision received June 12, 1989.

*Research Assistant, School of Mechanical Engineering, Ray W. Herick Laboratories. Currently at Nelson Industries, Stoughton, Wisconsin.

†Associate Professor, School of Mechanical Engineering, Ray W. Herick Laboratories. Member AIAA.

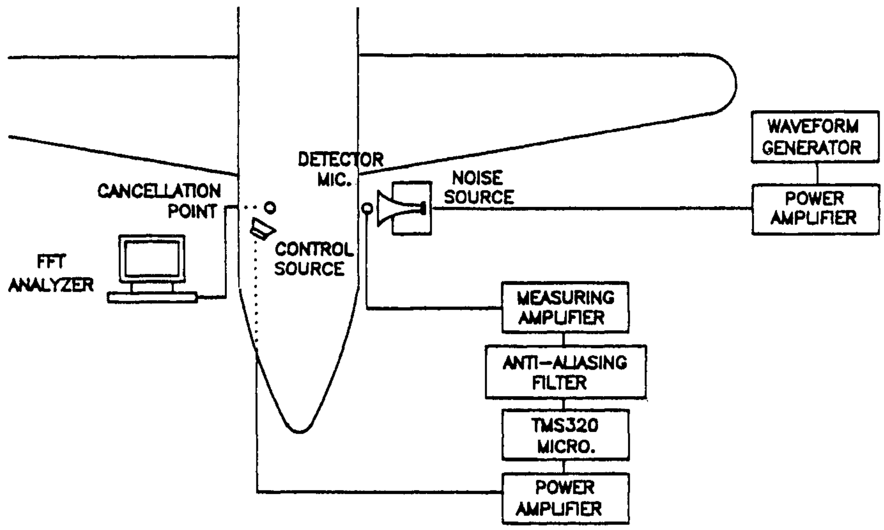

Fig. 2 Experimental setup for local cancellation in an 18-passenger aircraft.

tion occurs at P. As discussed by Swinbanks,[7] the responses at P and D can be expressed as a superposition of the two sources N and S, such that

$$P = P_n N + P_s S \tag{1}$$

$$D = D_n N + D_s S \tag{2}$$

where P_n and P_s are the transfer functions between the noise source and secondary source and the pressure at the cancellation point, and D_n and D_s are the transfer functions between the noise source and the secondary source and the pressure at the detector location. The transfer function P_s is referred to in this paper as the error path transfer function. If the acoustic feedback path, D_s, can be eliminated, equation (2) can be substituted into equation (1) to obtain

$$P = \frac{P_n}{D_n} D + SP_s \tag{3}$$

With the control source off, the ratio of transfer functions P_n and D_n is equivalent to the detector-cancellation point frequency response function, P_d.

For active noise control, the response at P should be zero. Thus, in the absence of significant acoustic feedback, the desired open-loop controller transfer function, H, can be written:

$$H = \frac{S}{D} = -\frac{P_d}{P_s} \tag{4}$$

For the test case, the transfer functions, P_d and P_s, in equation (4) are measured independently. P_s is measured with the noise source off. P_d is measured with the secondary source off. The ratio of the measured transfer functions is used to obtain the desired frequency response function of the controller.

A rational fraction polynomial (RFP) parameter estimation technique[8] was used to curve-fit the frequency response data of H to

$$H(s) = \frac{b_0 s^m + b_1 s^{m-1} + \cdots + b_m}{a_0 s^n + a_1 s^{n-1} + \cdots + a_n} \tag{5}$$

The information provided by the RFP curve-fit can also be represented in terms of modal parameters in the form of

$$H(s) = \sum_{k=1}^{N} \left[\frac{r_{ik} s + r_{ik} \zeta_k \omega_{nk} + r_{rk} \omega_{dk}}{s^2 + 2\zeta_k \omega_{nk} s + \omega_{nk}^2} \right] \tag{6}$$

where ω_n is the natural frequency, ω_d is the damped natural frequency, ζ is the damping ratio, and r_r and r_i are the real and imaginary parts of the complex modal residue. Since H is the result of the division of transfer functions, the modal parameters in Eq. (6) do not directly correspond to actual system modes. The controller is expressed in terms of modal parameters in order to allow for a relatively straightforward transformation to the discrete domain. Employing the Bilinear Transformation and by prewarping the continuous frequency response at the natural frequencies,[9] each second-order module associated with a natural frequency in the continuous domain transforms directly to a second-order recursive module in the discrete domain. The controller transfer function can be written as

$$H(z) = \sum_{k=1}^{N} \left[\frac{b_{0k} + b_{1k} z^{-1} + b_{2k} z^{-2}}{1 + a_{1k} z^{-1} + a_{2k} z^{-2}} \right] \tag{7}$$

The controller is implemented as a parallel recursive IIR digital filter. A detailed discussion of this modeling and implementation technique is presented by Warner.[10]

Test Results

Laboratory tests of the nonadaptive controller were performed in an 18-passenger Handley Page 137 Jetstream III airplane fuselage. Figure 2 shows the experimental setup. An Altec A7X loudspeaker was used in place of the left engine to simulate a noise source. To prevent control source-detector interaction, a microphone exterior to the fuselage served as a detector. A microphone monitoring the response at the cancellation point was placed in the propeller plane at a passenger's head location. The controller was implemented using a TMS320 microprocessor. The control output was amplified and used to drive the control source, which was located within inches of the cancellation point.

Figure 3 shows the frequency response of the required controller resulting from division of the appropriate measured transfer functions. Also shown is the frequency domain curve fit used to model the controller. The data was selectively curve fit to model only the dominant response peaks. Control was not attempted below 80 Hz due to the limited frequency response of the control speaker. The implemented controller in this case consists of 15 second-order recursive modules utilizing 75 filter coefficients.

A special swept-sine signal was used to drive the noise source. The controller reduced the sound power spectrum at the cancellation point as shown in Fig. 4. Figure 5 shows the corresponding noise reduction. These results indicate that substantial broadband noise reduction can be achieved using a relatively low-order filter. Although the system is well modeled between 370 and 420 Hz, the attenuation in this frequency range is relatively poor. Since temperature and humidity affect the speed of sound in air, it is believed that variations in these conditions from the time the system was modeled to the time the controller was tested account for the poor performance at these frequencies.

Controller performance was also tested using simulated propeller noise synthesized from an analog recording of turboprop engine noise. Figure 6 shows the controlled and uncontrolled spectra at the cancellation point up to 500 Hz. Note that harmonics lying in well modeled frequency ranges were attenuated 12–22 dB.

Adaptive Controller Simulation

No matter how accurately an acoustical system can be modeled using off-line techniques, in time, that system will in some way deviate from the model. Active noise control systems are typically time varying due to atmospheric and system changes and sensor or actuator wear. Inevitable system uncertainties also cause inaccuracies in offline models. Therefore, active noise controllers must be capable of adapting online in order to produce continual effective noise reduction in practical applications. Any of a variety of adaptive methods can be used. However, the adaptive controller must be implemented in a form that allows for accurate representation of the acoustic system, and the controller computation must be sufficiently fast to assure causality for a wide selection of sensor locations. The LMS and RLMS gradient based algorithms are adaptive methods with relatively low complexity, that have been shown to accurately model one-dimensional acoustic systems.[11,12]

Burgess[12] first introduced the idea of applying gradient search techniques to active noise control in 1981 by simulating the use of an LMS filter to estimate a simple plant. The control speaker and error microphone were modeled offline as second-order systems. Unfortunately, the characteristics of these components are often time varying, and a fixed model of the error path may not be appropriate. This paper presents a detailed simulation of LMS and RLMS adaptive, active-noise control systems utilizing a technique developed by Eriksson et al.[13] that allows for online error path modeling. Both pole-zero and all-zero models of the error path are considered. Application to aircraft is studied by simulating the airplane system discussed in the previous section of this paper.

There exists some uncertainty as to whether finite impulse response (FIR) or IIR filters are best for representing three-dimensional acoustic systems. Finite impulse response filters have been used extensively in active noise control—particularly in one-dimensional applications. However, despite their relative simplicity and inherent stability, the all-zero nature of

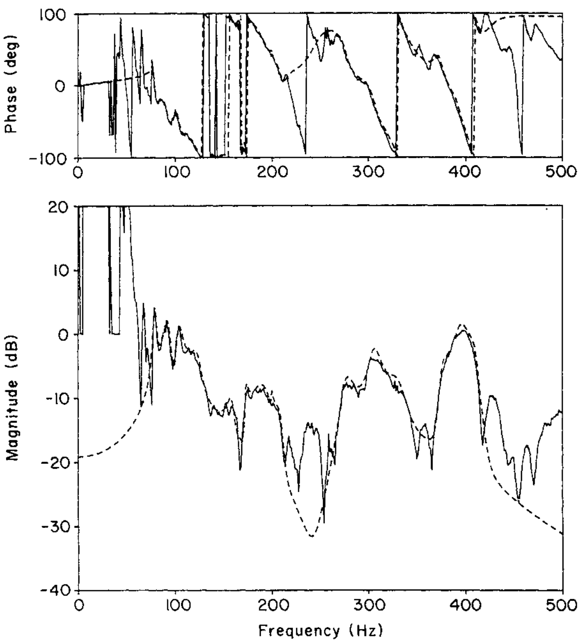

Fig. 3 Frequency response of the nonadaptive controller for local cancellation in the aircraft (—— desired response, ------ curve-fit model).

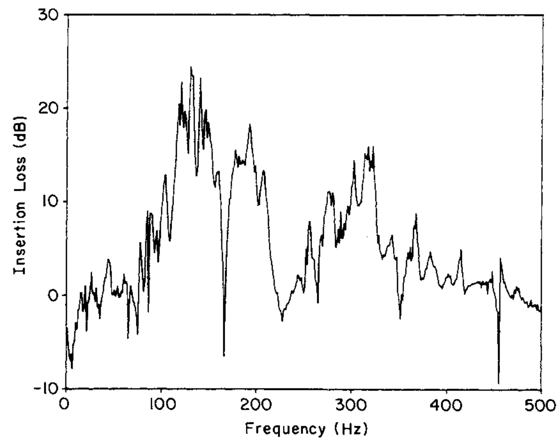

Fig. 5 Insertion loss corresponding to Fig. 4.

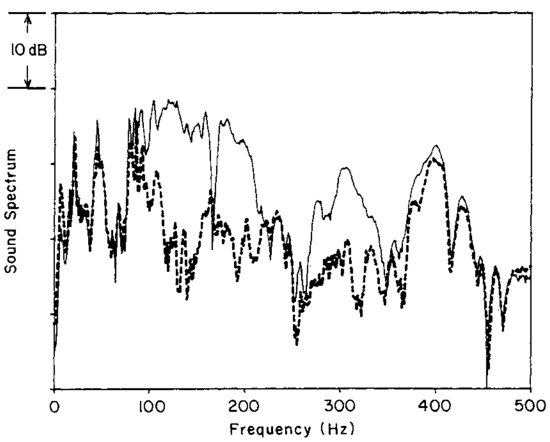

Fig. 4 Power spectra of broad-band noise at the cancellation point using the nonadaptive controller (—— controller off, ------ controller on).

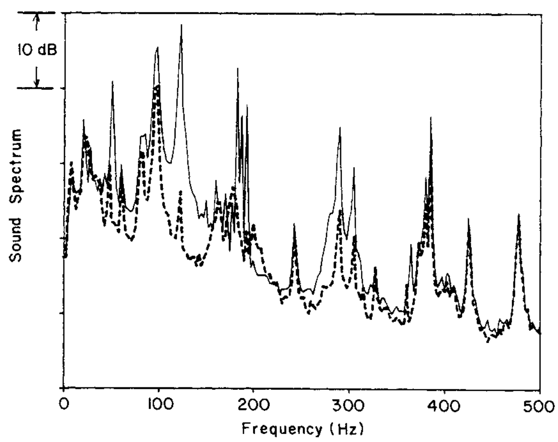

Fig. 6 Power spectra of synthesized turboprop engine noise at the cancellation point using the nonadaptive controller (—— controller off, ------ controller on).

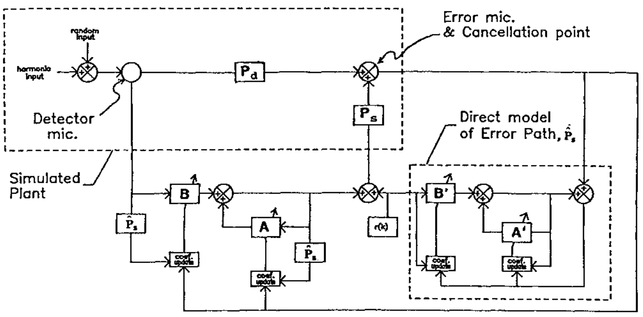

Fig. 7 Schematic for computer simulation of an RLMS adaptive sound controller in systems with no acoustic feedback.

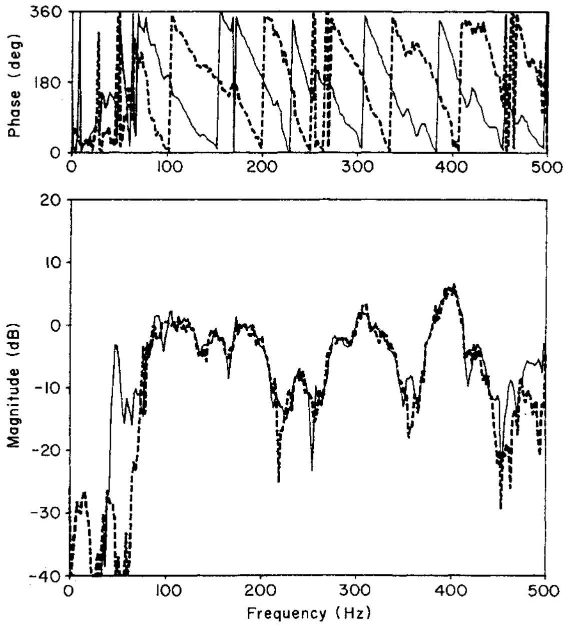

Fig. 8 Transfer functions of P and the adapted RLMS estimate of P for the simulated aircraft (________ actual response, ------ RLMS estimate using 35 coefficients in A and B and 10 coefficients in A' and B').

FIR filters prevents them from accurately modeling systems with dominant poles. As Eriksson[11] has demonstrated in a one-dimensional problem, the acoustic feedback caused by control source-detector interaction introduces poles in the system that must be removed in order to accurately model the plant. He advocates the use of an IIR filter configured in an RLMS structure. The acoustic feedback problem can be eliminated altogether in some cases by proper selection or positioning of sensors as has been previously shown. However, 3-D systems have much different dynamic behavior than 1-D systems and are commonly more reverberant. The impulse response of a 3-D system, therefore, can be very long and complicated requiring an FIR filter to have a prohibitively large number of filter coefficients in order to accurately model the system. Recursive IIR filter implementations have the ability in some instances to drastically reduce the high computational requirements of FIR filters while maintaining basically the same performance. The following simulation studies adaptive, active-noise control in an airplane and compares the performance of LMS and RLMS algorithms to determine whether there is a need for the additional complexity of a recursive algorithm.

Adaptive Active Noise Control Simulation

A block diagram of the adaptive active noise control system is shown in Fig. 7. The blocks labeled P_d and P_s represent plant

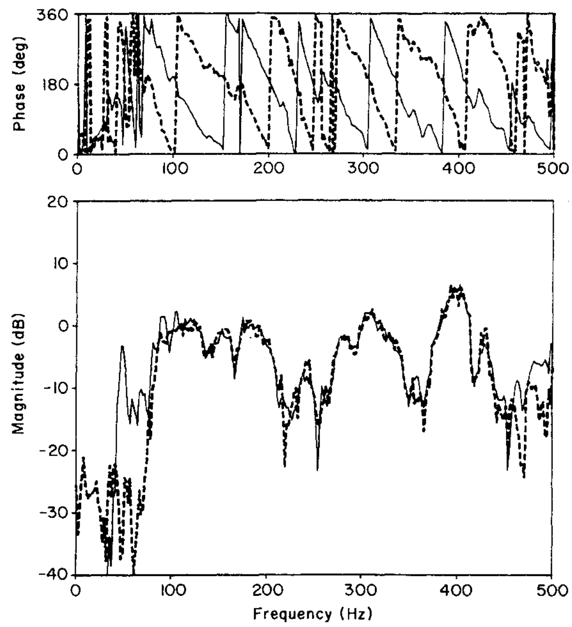

Fig. 9 Transfer functions of P and the adapted LMS estimate of P for the simulated aircraft (______ actual response, ------ LMS estimate using 70 coefficients in B and 20 coefficients in B').

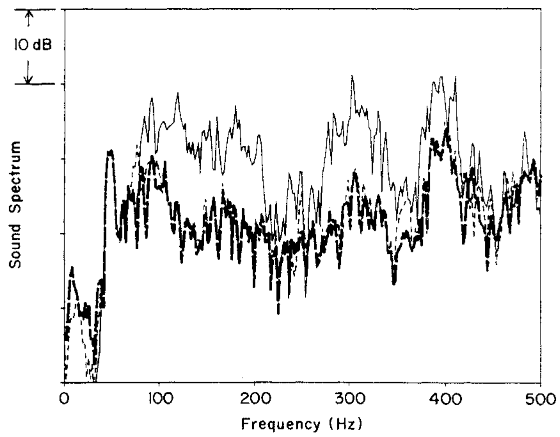

Fig. 10 Power spectra of random noise at the cancellation point in the simulated aircraft after 30,000 iterations (______ controller off, ------ RLMS controller on, — — — LMS controller on).

transfer functions of the detector-cancellation point path and the error path, respectively. The corresponding transfer functions used to model the nonadaptive controller were inverse Fourier transformed and inserted directly into the simulation. Therefore, the steady-state response of the real system including speaker, microphone, and amplifier dynamics is accurately simulated. Since no acoustic feedback occurred in the actual system, none is included in the simulation.

The blocks labeled A and B, together with their respective coefficient update algorithms, comprise the RLMS estimator proposed and demonstrated by Feintuch.[14] The A is the feedback or recursive process, and B is the feedforward or nonrecursive process. An LMS estimator is obtained by omitting feedback process A. The transfer function of the error path must be included in the coefficient update algorithm in order to compensate for its effect. A model of the error path, $\hat{P}_s$, is determined online with an adaptive RLMS estimator similar to the plant estimator. A low amplitude pseudorandom signal, $r(k)$, is injected into the control source as an uncorrelated training signal for the error path estimator. The convergence parameters used in the coefficient update algorithms are scaled using the power of the filter input signal as discussed by Burgess.[12]

Simulation Results

For proper noise cancellation, the estimator must converge such that the control loop, which consists of the estimator and the error path, produces a disturbance at the error microphone equal and opposite to the noise due to the primary source. Figure 8 compares the transfer function of P to the transfer function of the converged control loop using an RLMS plant estimator with 35 feedforward and 35 feedback filter coefficients. The error path estimator used 10 feedforward and 10 feedback filter coefficients. The response of the converged estimator is opposite in phase from the plant as was expected. Using 70 coefficients to model the plant and 20 coefficients to model the error path, the LMS algorithm produced the plant estimate shown in Fig. 9. In all the simulations run using the airplane system, the LMS estimator was able to model the plant as accurately as the RLMS estimator using the same total number of filter coefficients. The resulting attenuation of broadband random noise for both algorithms with these filter lengths is similar as shown in Fig. 10. However, in the presence of acoustic feedback, it is expected that the RLMS estimator would perform considerably better than the LMS estimator.

A consequence of the counter-rotating designs of advanced turboprop engines is that the noise spectra contain many more harmonics than conventional turboprop engines. For cancellation systems which control each harmonic individually, a very large controller may be required. Alternatively, broadband control techniques like the adaptive methods presented in this paper will not require any increase in complexity regardless of how many harmonics the noise field includes. A signal containing 35 harmonics was added to random noise with a 40 dB signal-to-noise ratio and was used as a primary source in the simulation. Using an RLMS filter with 35 feedforward and 35 feedback coefficients in the plant estimator and 10 feedforward and 10 feedback coefficients in the error path estimator, an overall insertion loss of 10.9 dB was achieved. Most harmonics were attenuated by at least 20 dB as shown in Fig. 11. An LMS filter with the same total number of coefficients produced better results with an overall insertion loss of 12.6 dB. Most harmonics were attenuated by more than 30 dB. The controlled power spectrum is also shown in Fig. 11. Since the control speaker response is poor below 100 Hz, neither algorithm performed well in this frequency range. Attenuation was relatively poor for both algorithms at high frequencies.

Finding an optimum filter length for a particular system seems to be a trial and error process. Although convergence properties of the RLMS algorithm are not well known, it is generally understood that the filter must be of sufficient size in order for there to exist only a single global minimum. However, if the filter is overspecified, unused pole-zero pairs can migrate to the unit circle causing stability problems.[15] Figure 12 compares plots of mean squared error at the cancellation point of the airplane system for three RLMS systems with different total filter lengths. Notice how the lowest-order system with only 30 coefficients seems to have converged to a relatively poor minimum. Figure 13 shows a similar plot for three different LMS filters. Notice how the system with 90 total coefficients has reached the same minimum as the system using 140 total coefficients.

Practical Limitations of Adaptive Digital Filter Implementation

One of the major problems involved in practical implementation of digital active noise controllers is proper positioning of detector transducers with respect to the cancellation point. There exist two conditions for causal control of the direct sound field. First, the detector must be located closer than the cancellation point to the noise source. For most active noise control applications, this requirement is relatively easy to achieve. However, causality also requires that the propagation delay associated with the detector-cancellation point path be greater than the control loop delay. Therefore, the detector must be placed outside a specified radius from the cancellation point.

The control loop delay consists of the delays due to the microprocessor sampling process and the associated antialiasing and smoothing filters as well as the error path propagation

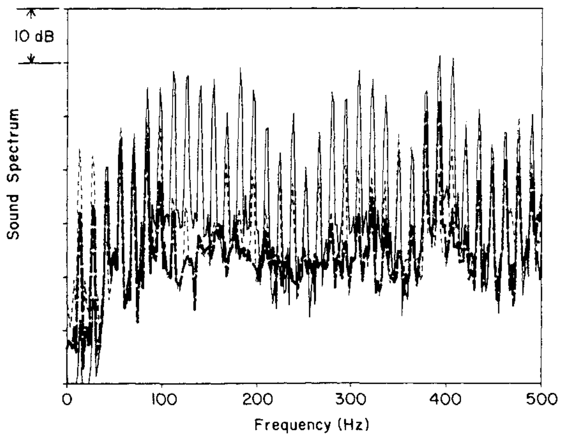

Fig. 11 Power spectra of a noise corrupted harmonic signal (40 dB snr) at the cancellation point in the simulated aircraft after 100,000 iterations (______ controller off, ------ RLMS controller on, — — LMS controller on).

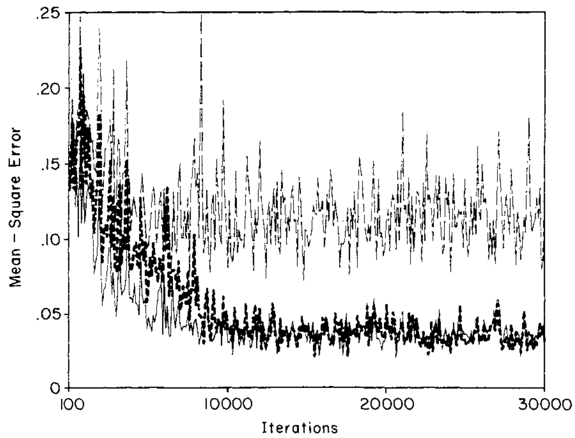

Fig. 12 Reduction of mean squared error over time for different RLMS filter lengths (______ 90 total coefficients, ------ 140 total coefficients, — — — 30 total coefficients).

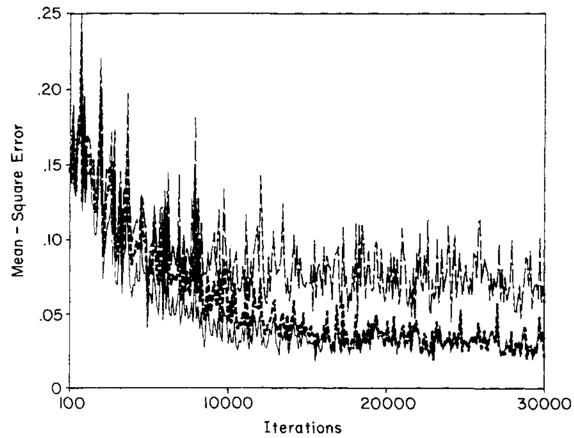

Fig. 13 Reduction of mean squared error over time for different LMS filter lengths (______ 90 total coefficients, ------ 140 total coefficients, — — — 30 total coefficients).

delay. Assuming that the control speaker is placed within one foot of the cancellation point and that the phase delay of the speaker and error microphone are negligible, the error-path delay is less than 1 ms. The microprocessor sampling delay depends on the complexity of the controller. For an RLMS system using 70 coefficients in the plant estimator and 20 coefficients in a direct estimator for the error path, computations for each sample should be completed in less than 200 μs on a TMS32020 microprocessor allowing for a sample rate as high as 5 kHz. The phase delay of the antialiasing and smoothing filters for a particular cutoff frequency obviously depends on their order. For example, the delay of a Wavetek Model 852 Hi/Lo pass filter in flat delay mode is $1/f_c$ where f_c is the cutoff frequency in Hz. Since the cutoff frequency of the antialiasing filter determines the frequency range that the adaptive filter must model, the cutoff frequency for each filter would be set to 500 Hz for most active noise control applications. The two analog filters, then, contribute 4 ms delay, and the total control loop delay becomes 5.2 ms corresponding to a propagation distance of 5.85 feet. In order for the system to cancel random noise, the detector must be outside of this radius from the cancellation point. In some circumstances, such a configuration will not be possible. For deterministic signals, these considerations are not relevant.

Conclusions

Two studies have been presented for local cancellation of sound in three-dimensional enclosures using digital filtering techniques. The first study demonstrated the feasibility of recursive filters for control of sound fields in an airplane cabin. The study utilized a rational fraction polynomial curve-fitting technique to model the frequency response of a controller derived from measured system transfer functions. An IIR digital filter designed from the frequency domain model was used to implement the control. The controller produced broadband, random noise reductions of 10–20 dB over a substantial frequency range when used to cancel sound at a seat location in an 18-passenger stationary aircraft.

However since environmental conditions have significant influence on the system response, a control system using adaptive digital filtering techniques was studied using a simulation program. The control system allowed for online adaptive modeling of the control source-cancellation point path. By incorporating impulse response measurements of the airplane system in the simulation, control capabilities of LMS and RLMS gradient-based adaptive algorithms in aircraft applications were studied in detail. In the absence of acoustic feedback, it was found that the all-zero LMS algorithm was able to model the airplane system as well as the pole-zero RLMS algorithm using the same total number of filter coefficients. Although definitely a pole-zero system, the airplane interior contains enough damping for it to be modeled well with an FIR filter. Both algorithms attenuated broadband random noise by at least 10 dB over a broad frequency range. The LMS algorithm was superior to the RLMS algorithm in reducing a rich harmonic sound field. Over 30 dB attenuation was achieved at most blade passage frequencies using an LMS filter, whereas the RLMS filter attenuated most harmonics by 20 dB.

Antialiasing and smoothing filters necessary for the sampling process introduce substantial control loop delay, which, for control of nondeterministic signals, forces the detector transducer to be placed outside a radius of several feet from the cancellation point. This suggests that detectors be located exterior to the fuselage provided the noise source can be accurately observed.

Acknowledgments

This work was supported by NSF Grant MSM 8505834.

References

[1]Chase, V. D., "Propfans—A new twist for the propeller," *Mechanical Enginering,* Nov. 1986, pp. 47–50.

[2]Bullmore, A. J., Nelson, P. A., and Elliott, S. J., "Active Minimization of Acoustic Potential Energy in Harmonically Excited Cylindrical Enclosed Sound Fields," AIAA Paper 86-1958, July 1986.

[3]Lester, H. C., and Fuller, C. R., "Active Control of Propellent Induced Noise Fields Inside a Flexible Cylinder," AIAA Paper 86-1957, July 1986.

[4]Zalas, J. M., and Tichy, J., "Active Attenuation of Propeller Blade Passage Noise," NASA CR-172386, July 1984.

[5]Abler, S. B., and Silcox, R. J., "Experimental Evaluation of Active Noise Control in a Thin Cylindrical Shell," *Proceedings of Noise-Con 87,* Pennsylvania State University, 1987, pp. 371–376.

[6]Jones, J. D., and Fuller, C. R., "Effects of an Internal Floor on Low Frequency Sound Transmission into Aircraft Cabins—An Experimental Investigation," AIAA Paper 86-1939, July 1986.

[7]Swinbanks, M. A., "Active Noise and Vibration Control," Fortschritie der Akustik-DAGA '85 (Stuttgart), DPG-Kongress-GmbH, Bad Honnef, 1985, pp. 87–101.

[8]Richardson, M. H., and Formenti, D. L., "Parameter Estimation from Frequency Response Measurements using Rational Fraction Polynomials," Structural Measurement Systems, Inc., San Jose, CA, Technical Note 85-3, 1985.

[9]Phillips, C. L., and Nagle, H. T., Jr., *Digital Control System Analysis and Design,* Prentice-Hall, Englewood Cliffs, NJ, 1984.

[10]Warner, J. V., "Active Control of Sound Fields in Three-Dimensional Enclosures," M.S. Thesis, Purdue University, West Lafayette, IN, 1987.

[11]Eriksson, L. J., Allie, M. C., and Greiner, R. A., "The Selection and Application of an IIR Adaptive Filter for Use in Active Sound Attenuation," *IEEE Transactions: Acoustics, Speech and Signal Processing,* Vol. 35, No. 4, 1987, pp. 433–437.

[12]Burgess, J. C., "Active Adaptive Sound Control in a Duct: A Computer Simulation," *Journal of the Acoustical Society of America,* Vol. 70, No. 3, pp. 715–726.

[13]Eriksson, L. J., and Allie, M. C., "The Use of Random Noise for On-Line Transducer Modeling in an Adaptive Active Attenuation System," *Journal of the Acoustical Society of America,* Vol. 80, No. S1, 1986, p. S11.

[14]Feintuch, P. L., "An Adaptive Recursive LMS Filter," *Proc. IEEE,* Vol. 64, Nov. 1976, pp. 1622–1624.

[15]Parikh, D. D., "Time Domain IRR Adaptive Digital Filtering Algorithms," *24th Midwest Symposium on Circuits and Systems,* University of New Mexico, Albuquerque, NM, 1981, pp. 33–37.