

Adaptive active noise control in a duct using multiple models

다중 모델 기법을 이용한 덕트에서의 적응능동소음제어

Jae-myun Yang*, Chan-Soo Chung**, Hyun-do Nam***

양재민*, 정찬수**, 남현도***

ABSTRACT

The adaptive active control algorithm for duct noise attenuation is considered.

A duct is modelled using the superposition property when the acoustic feedback exists. All of the models of active noise control in ducts considered here are consistent. A new algorithm to estimate the secondary path transfer function (between the loudspeaker and the error microphone) using multiple models is presented. The computational burden of the proposed algorithm is much smaller than the existing methods, so it could be applied to the multi-channel cases.

Computer simulations were done to show the effectiveness of the proposed algorithm in a duct case.

요약

덕트에서의 능동소음감쇄 문제를 다루었다.

음향귀환이 있는 경우의 덕트를 중첩의 원리를 이용하여 모델링하였다. 본 논문에서 다루어진 능동소음제어를 위한 덕트 모델은 consistent하다고 가정했다. 스피커와 오차 마이크로폰 사이의 2차 경로 전달함수를 추정하기 위한 새로운 알고리즘을 제안했으며 제안된 알고리즘은 기존의 알고리즘보다 계산량이 작아 다중 채널 능동소음제어에도 이용될 수 있으리라 생각된다.

제안된 알고리즘의 효율성을 보이기 위하여 컴퓨터 시뮬레이션을 행했다.

1. Introduction

The benefits of using electronics to actively attenuate low frequency noise (approximately 500 Hz and below) have been recognised for some time [1]. An early proposal for active attenuations is in a patent by Lueg [2] using a technique which is still in use today.

Early researchers into noise control confined themselves almost solely to laboratory models of

ventilation ducts. This is due to the fact that ducts present the simplest problems as they are an one dimensional system capable of guiding plane (below cut-on) waves. Lueg's proposal for obtaining phase opposition of the input wave was, from a practical point of view, unsuccessful, largely due to problems of feedback.

using the advances in control systems technology and improved understanding of the physics of acoustic systems, many applications of ANC were presented [3,4]. Lueg's system used a single loudspeaker, and so is sometimes called the acoustic monopole system. Multiple loudspeaker

*Seoul National Polytechnic University

**Department of Electrical Engineering Soongsil University

***Department of Electrical Engineering Dankook University

systems have been used to overcome the frequency dependent problems of control design[3]. However, they have geometry related limitations. Because of these limitations and the capability of modern electronic systems to implement complex controllers, the current trends is to use the acoustic monopole.

In practical situations, the characteristics of the system to be controlled as well as the primary noise characteristics can be changed with time. In this case, an algorithm which simultaneously performs identification and control must be used [5,6]. Since these approaches require knowledge of the secondary path transfer function, some adaptive algorithms which simultaneously estimate the transfer function of a secondary path have been presented[5,6]. Such techniques are difficult to be applied to the multiple sensor multiple speaker cases because there are too many parameters to be estimated in each step.

In this paper, the models for active noise control in ducts using the superposition property. And a new algorithm to estimate the secondary path transfer function to reduce the computational burden was presented. Multiple models[7, 8] were used for identification of the secondary path transfer function and the IIR structure was used for the control filter. Since this approach requires only a small amount of computation, it may also be used in the multiple channel case.

II. Feedforward ANC problem in a duct

Active noise control (ANC) techniques can be divided into two types: one is a feedforward technique and the other is a feedback technique [1]. The feedback control approach can be implemented without knowledge of information on the primary noise characteristics, but this controller attenuates not only unwanted noises but also all other sounds such as speech. The feedforward control approach is applicable when a reference signal can be generated which is related to the sound radiated by the primary

source. The schematic diagram of the feedforward noise control system is shown in fig. 1.

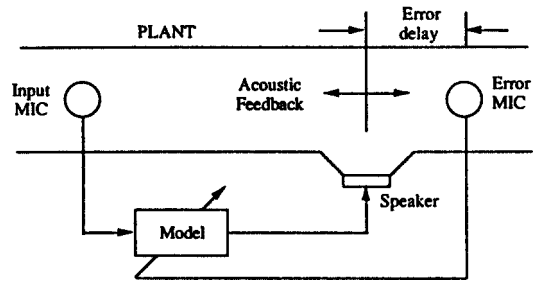


Fig. 1 Schematic diagram of the feedforward ANC system

This structure can be implemented using adaptive signal processing techniques which has been developed rapidly over the past few decades. An active sound attenuation system where an adaptive digital filter is used as the feedforward controller is shown in fig. 2.

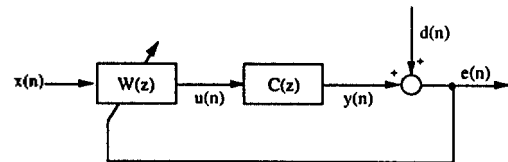


Fig. 2 Block diagram of the ANC system

The ideal control filter which, in the absence of measurement noise and any causality constraints, drives $e(n)$ to zero, is given by

$$W_R(z) = -\frac{D(z)}{C(z)} \quad (1)$$

If the plant is linear and if the plant and the control filter are time-invariant or slowly time-varying compared to the combined memory times or time constants of the adaptive filter and the plant, the order can be changed as shown in fig. 3.

Assume the signals are sampled and that the controller has a finite impulse response. The error in figure 3 can be represented by

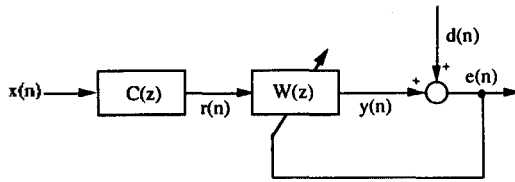


Fig. 3 Modified block diagram of the ANC

$$e(n) = \sum_{i=0}^p w_i r(n-i) \quad (2)$$

where the second term is the discrete convolution of the controller filter coefficients w_i with the filtered reference signal, $r(n)$, which may be written as

$$e(n) = d(n) + \underline{w}^T \underline{r}(n) \quad (3)$$

where

$$\underline{w} = [w_0, w_1, \dots, w_p]^T \quad (4)$$

$$\underline{r}(n) = [r(n), r(n-1), \dots, r(n-p)]^T \quad (5)$$

The cost function in this case is

$$\begin{aligned} J &= E[e^2(n)] \\ &= E[d^2(n) + \underline{w}^T \underline{r}(n)d(n) + d(n)\underline{r}^T(n) \\ &\quad \underline{w} + \underline{w}^T \underline{r}(n)\underline{r}^T(n)\underline{w}] \end{aligned} \quad (6)$$

a quadratic form in the vector \underline{w} minimised by

$$\underline{w}_{opt} = -E[\underline{r}(n)\underline{r}^T(n)]^{-1}E[\underline{r}(n)d(n)] \quad (7)$$

where $\underline{r}(n)\underline{r}^T(n)$ is a matrix of autocorrelations of $\underline{r}(n)$ and $\underline{r}(n)d(n)$ is a vector of cross-correlations between $\underline{r}(n)$ and $d(n)$.

This form of solution is called the Wiener filter. Adaptive algorithms such as the "filtered-x LMS" can be used to iteratively adjust the coefficients of \underline{w} , so that the mean square error is minimised, and this optimum can be approached in practice.

It gives a minimum value of

$$\begin{aligned} J_{min} &= E[d^2(n)] - E[\underline{r}^T(n)d(n)]^T \\ &\quad E[\underline{r}(n)\underline{r}^T(n)]^{-1}E[\underline{r}(n)d(n)] \end{aligned} \quad (8)$$

The importance of this time domain analysis is that it allows the constraints of causality and finite filter length to be imposed on the analysis, allowing off-line prediction of the reductions achievable from a practical controller.

The filter coefficient vector $\underline{w}(n)$ can now be updated using the LMS algorithm[9]

$$\underline{w}(n+1) = \underline{w}(n) - 2\mu e(n)\underline{r}(n) \quad (9)$$

where μ is the convergence parameter that controls the rate of convergence.

If $C(z)$ is unknown or time-varying, $C(z)$ must be identified to apply the filtered-x LMS algorithm. Elliott et al.[4] used off-line estimation of $C(z)$, i.e. it can be estimated before installation for a particular setting and fixed thereafter.

In many practical applications, $C(z)$ could be changed with time, for example temperature and flow changes in the duct result in sound velocity change in the system. In this case, the adaptive active control algorithm which estimates the parameters of $C(z)$ and adjusts the filter parameters simultaneously should be applied.

III. Control filters using multiple model approach

Eriksson et al.[5,6] introduced an adaptive active noise control algorithm which continuously estimates the secondary path transfer function using the LMS algorithm. They have investigated the use of a single recursive (IIR) filter as the controller in a duct, continuously updated using an adaptive algorithm as shown in figure 4.

The algorithm used an estimate of the transfer function from the secondary source to error microphone which is continuously estimated "on line" with a low level identification signal which is also fed to the secondary source. But the computation burden of this algorithm increases in

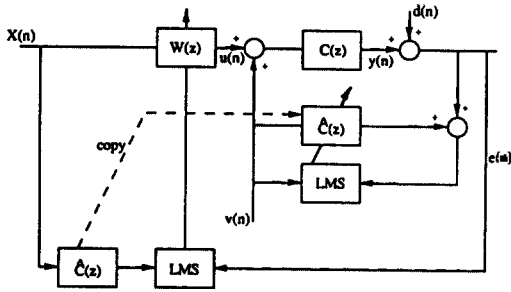


Fig. 4 Continuous identification algorithm

proportion to the square of the number of channels. It is thus very difficult to apply these algorithms to multi-channel cases, when the number of channel is large.

To overcome these difficulties, we present the multiple-model adaptive algorithm to identify the secondary path transfer function. This algorithm does require some *a priori* information about the behavior of the plant, but it involves a relatively small computational burden. It may thus be easier to apply to multi-channel cases.

Most approaches of MMAC thus use multiple controllers, previously designed to control each of the assumed models of the plant. In the current work, we propose to use multiple models of the plant to update an infinitely adaptable feed forward controller. Multiple-models are thus used in the identification routine to estimate the secondary path transfer function as shown in Fig. 5, in

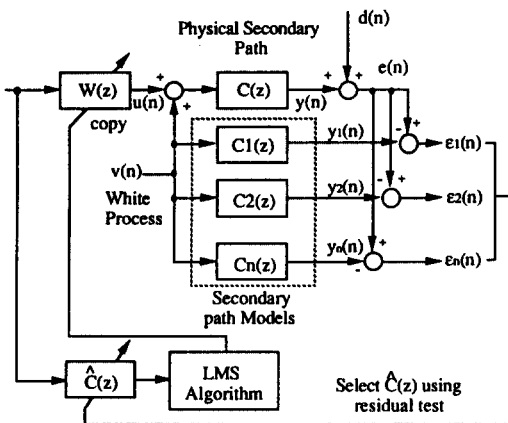


Fig. 5 Multiple model adaptive controller

which the secondary path transfer function is estimated using the multiple-model techniques and then used in the adjustment of the control filter coefficients.

The output of i -th model is

$$y_i(n) = C_i(z)v(n) \quad (10)$$

where $v(n)$ is an identification noise which is usually a white process. The residual error of the i -th model is thus

$$\epsilon_i = e(n) - y_i(n) \quad (11)$$

where $e(n)$ is the output of the error microphone, which is itself

$$e(n) = C(z)(u(n) + v(n)) \quad (12)$$

in which $u(n)$ is the output of the control filter.

The residual error for the i -th model can thus be written as

$$\epsilon_i(n) = C(z)u(n) + (C(z) - C_i(z))v(n) \quad (13)$$

Assuming that $v(n)$ is uncorrelated with $u(n)$, the mean square value of this error will have a component proportional to the mean square value of $u(n)$, which will not be affected by $C_i(z)$, and another component proportional to the mean square value of $v(n)$, which will depend on the difference $C(z) - C_i(z)$. The mean square error will clearly be a minimum if this difference is zero i.e. $C_i(z) = C(z)$.

The power of the i -th residual error can, in practice, be estimated using the equation

$$PE_i = \sum_{j=n-D}^n \epsilon_i^T(j) \epsilon_i(j) \quad (14)$$

where D is a memory length.

The procedure for MMAC is as follows :

- (i) Construct n models for expected variations of the second path, for example change in the sound propagation speed due

to the temperature change in a duct.

- (ii) Calculate PE_i for each model.
- (iii) Select the model which has the minimum residual power.
- (iv) Use this model coefficients in the controller.

As shown in equation (1), the ideal control filter $W_R(z)$ should have poles to remove the poles of the overall model. Eriksson et al.[5,6] also showed that an IIR structure for the control filter is more effective than the FIR structure when the acoustic feedback exists. If the FIR structure is used in these cases, the length of the FIR filter should be very large when the poles of that should be removed are near the unit circle. The adaptive recursive least mean squares (RLMS) algorithm introduced by Feintuch[10] was used to adjust the control filter coefficients.

IV. Models for ducts

A reasonably general representation of an active noise control system in a duct is given in figure 6.

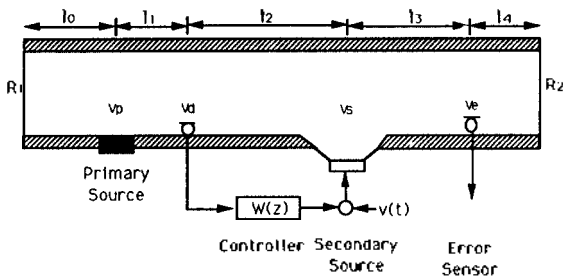


Fig. 6 Representation of a duct

The left and right ends of the duct have complex pressure reflection coefficients R_1 and R_2 respectively, and $v(t)$ is an identification signal. It is assumed that only plane waves propagate in the duct and also that the sources and the sensor are sufficiently far apart that near field effects can be ignored.

This system has two electrical inputs: V_p and V_s which drive the primary and secondary

source, and two electrical outputs, V_d and V_e , from the detection sensor and the error sensor. If all components in the system are linear, the output voltage V_e can be obtained as

$$V_e = D(z)V_p + C(z)V_s \quad (15)$$

$$V_d = B(z)V_p + F(z)V_s \quad (16)$$

The assumption of linearity leads directly to an equivalent block diagram for this system in which each element describes an electrical transfer function, as in figure 7.

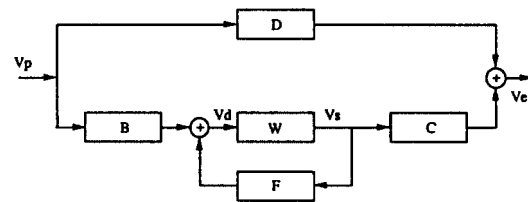


Fig. 7 Block diagram of the ANC system in a duct

Using the standard steady state travelling wave theory to this system, the transfer functions $C(z)$, $D(z)$, $B(z)$ and $F(z)$ can be derived by [11]

$$C(z) = \left[\frac{V_e}{V_s} \right]_{V_p=0} = \frac{H_s H_e e^{-k l_3} [1 + D_e R_2 e^{-2k l_4}]}{[1 - R_1 R_2 e^{-2k l}]} \times [1 + D_s R_1 e^{-2k(l_0 + l_1 + l_2)}] \quad (17)$$

$$D(z) = \left[\frac{V_e}{V_p} \right]_{V_s=0} = \frac{H_e H_p e^{-k(l_1 + l_2 + l_3)} [1 + D_e R_2 e^{-2k l_4}]}{[1 - R_1 R_2 e^{-2k l}]} \times [1 + D_p R_1 e^{-2k l_0}] \quad (18)$$

$$B(z) = \left[\frac{V_d}{V_p} \right]_{V_s=0}$$

$$= \frac{H_d H_p e^{-k(1_1)} [1 + D_d R_2 e^{-2k(1_2+1_3+1_4)}]}{[1 - R_1 R_2 e^{-2k1}]}$$

$$\times [1 + D_p R_1 e^{-2k1_0}] \quad (19)$$

$$F(z) = \left[\frac{V_d}{V_s} \right]_{V_p=0}$$

$$= \frac{H_d H_s R_1 R_2 e^{-k(2l_1-1_2)} [1 + D_d / R_1 e^{-2k(1_0+1_1)}]}{[1 - R_1 R_2 e^{-2k1}]}$$

$$\times [1 + D_s / R_2 e^{2k(1_3+1_4)}] \quad (20)$$

A summary of the terminology is given in table 1.

Table 1. The definition of the transducer symbols

	Primary Source	Secondary Source	Detection Sensor	Error Sensor
Input or Output Voltage	V_p	V_s	V_d	V_e
Electroacoustic Transfer fn.	H_p	H_s	H_d	H_e
Directivity Factor	D_p	D_s	D_d	D_e

V. Computer simulations

We assume that only the speed of sound changes with time, to simplify the problem. When the sound speed and/or the temperature

and flow etc. change with time, this algorithm can be applied by increasing a number of plant models.

The speed of sound changes from 330(m/s) to 350(m/s) as shown in figure 8. 3 Secondary path models which are correct for sound speeds of 330 (m/s), 340(m/s) and 350(m/s) were used. And the memory length D set to 1000 samples.

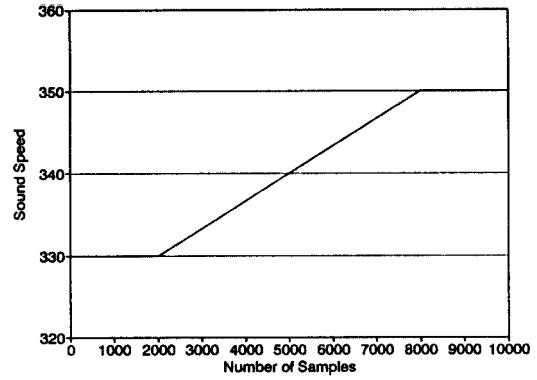
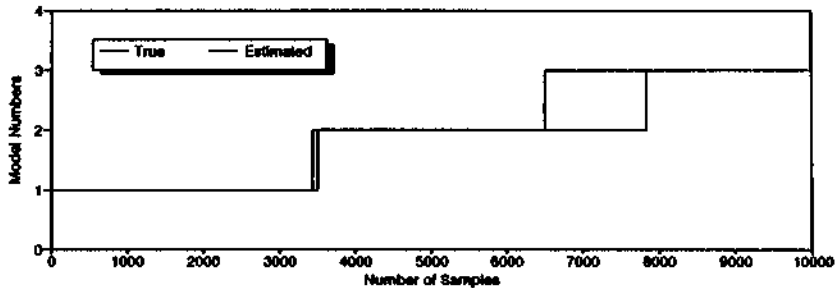
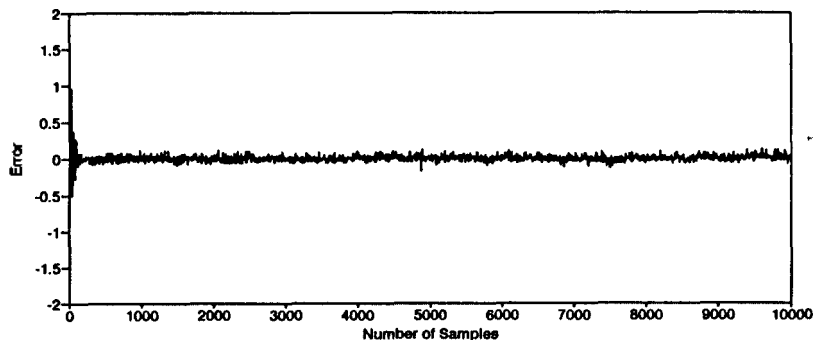


Fig. 8 Sound speed

The results are shown in figures 9. It can be seen that the model number is correctly estimated by the algorithm most of the time, although the primary source acts as noise in this process. The most important result of this simulation is that the control system remains stable over this change in sound speed.



(a) True and Estimated Model Number



(b) Error

Fig. 9 Estimated model number and errors

VI. Conclusions

In this research, the adaptive active noise control algorithm for duct noise attenuation was considered. The superposition model was used for modelling ducts. This model has the advantage that it always has the relationship with electrical quantities (voltage), and thus the variables are directly measurable. The new identification algorithm for the secondary path transfer function using the multiple model approach using multiple models.

The proposed algorithm could be used for multiple channel cases because the decision process is independent of the number of channels in this method.

Computer simulations was done to show the effectiveness of the proposed algorithm in a duct case.

References

1. Elliott S.J. and Nelson P.A., "The active control of sound," *Electronics and Communication Eng. Jour.*, pp.127-136, 1990.
2. Lueg P., "Process of silencing sound oscillations," US Patent 2 043416, 1934.
3. Swinbanks M.A., "The active control of sound propagation in long ducts," *Journal of Sound and Vibration*, 27(3), pp.411-436, 1973.
4. Elliott S.J., Stothers I.M. and Nelson P.A., "A multiple error LMS algorithm and its application to the active control of sound and vibration," *IEEE Trans. Acoust., Speech, Signal Processing*, Vol. ASSP-35, No.10, pp.1423-1434, 1987.
5. 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 Trans. on Acoust. Sound and Signal Processing*, Vol. ASSP-35, No.4, pp.433-437, 1987.
6. Eriksson L.J. and Allie M.C., "Use of random noise for on-line transducer modelling in an adaptive active attenuation system," *J. Acoust. Soc. Am.*, 85(2), pp.797-802, 1989.
7. Nam H.D. and Elliott S.J., "Multiple model adaptive systems for active noise attenuation," *Proc. IEEE Workshop on Appl. Signal Proc. to Audio & Acoustics*, N.Y., 1991.
8. Nam H.D. and Elliott S.J., "Adaptive active attenuation of noise using multiple model approaches," submitted to *Mechanical Systems and Signal Processing*, 1992.
9. Widrow B. and Stearns S.D., *Adaptive Signal Processing*, Englewood Cliffs, NJ : Prentice-Hall, 1985.
10. Feintuch P.L., "An adaptive recursive LMS filter," *Proc. IEEE*, Vol. 64, No. 11, pp.1622-1624, 1976.
11. Elliott S.J. and Nelson P.A., "Models for describing active noise control in ducts," ISVR Technical Report No.127, University of Southampton, U.K., 1984.

A part of this research was carried out during Hyun-Do Nam's stay at the University of Southampton, which had been supported by the Korea Science and Engineering Foundation

professor. From January 1991 to January 1992, he was a visiting fellow at the Institute of Sound and Vibration Research, University of Southampton, England. His fields of interest are in Adaptive Signal Processing and Control and Active Control of Sound.

▲Jae-myun Yang



Jae-myun Yang was born in Taejeon, Korea, on February 25, 1936. He received the B. S. and M.S. degrees in Electrical Engineering from Yonsei University in 1960 and 1976, respectively.

From 1963 to 1977, he was a Professor at the department of Electrical Engineering, Taejeon Technical Junior College. From 1977 to 1983, he worked as the Senior Researcher at the Ministry of Education. During 1983-1987, he was a Dean of the Cheonam Technical Junior College. Since 1987, he has been with the Institute of Industrial Education, Seoul Polytechnic University, Seoul, Korea, where he is an assistant professor. He is currently working towards the Ph.D. degree in Dankook University.

His research interests are in Signal Processing and Control.

▲Chan-soo Chung Vol. 11 No. 6

▲Hyun-do Nam



Hyun-do Nam was born in Yecheon, Korea, on March 27, 1956. He received the B.S., M.S. and Ph.D. degrees in Electrical Engineering from Seoul National University in 1979, 1981 and 1986, respectively.

Since March 1982, he has been with the Department of Electrical Engineering, Dankook University, Seoul, Korea, where he is an associate