Neural Network Control on the Acoustic Field in a Duct

Kuo-tsai Chen, Bore-chien Tsai, Sue-min Huang, Jean-Hong Chou, Su-Hua Chang
Department of Engineering Science and Ocean Engineering, National Taiwan University
1 sect.4 Roosevelt Rd., Taipei, R.O.C. in Taiwan
E-mail: ktchen@ccms.ntu.edu.tw

ABSTRACT

This paper is a new try to the study on the active noise control in duct by combining a control theory with an artificial-intelligence neural network (AINN).

The convergence of acoustic field being actively controlled in duct by computer simulation is firstly investigated. Using the result as obtained can obtain the optimum parameter of the artificial neural network used for the required experiment.

In experiment, two setups are adopted. The first one takes the signals directly from the function generator as the reference input of the control system. The result reveals the attenuation by more than 25 and 20 dB in residual acoustic pressure and its associated power for pure- and dual-tone sounds. The second one places the reference microphone in a passive device to directly measure the signal downstream the primary source. The device as above mainly alleviates the influence of the acoustic feedback produced by the secondary source on the input microphone. Its experimental result shows the reduction by more than 30 or 20 dB for the same acoustic quantities as that of the first one.

INTRODUCTION

Regarding the noise control in the application of acoustics, it is from past studies[1-8] to show that the active control technique can provide better effectiveness than the passive one at lower frequency. Specially speaking to the active control of sound propagation in duct, the past studies involved [2-9] revealed that the combination of either an adaptive or a robust control with some appropriate algorithms was usually used for getting better control effectiveness.

In recent years, the theory and applications of neural networks[10-20] for various kinds of fields, which include industrial control systems, artificial intelligence in engineering design, and economics and management science, etc., are, respectively, developed. Taking the application of neutral network control to duct acoustics into consideration, Chou[21] started the study involved in his master thesis. In this paper, it intends to study the active noise control in duct by combining a control theory with an artificial-intelligence neural network (AINN). The contents of study include the determination of optimum parameters for the artificial neural network to be used and the required experiment. From the experimental result as obtained, it shows the two frameworks adopted for reducing acoustic feedback provide almost the same attenuation of at least 20 decibels in acoustic downstream power.

THEORETICAL BACKGROUND

From the text of acoustics[1], the acoustic pressure generated by a point source in a duct of diameter smaller than that for cutoff frequency[1] must be of plane wave type, and can be expressed in terms of either a forward or a backward going plane wave fields as:

$$p(x) = \frac{\rho_o c_o q e^{-jk|x-x_o|}}{2S} \tag{1}$$

Where ρ_o, c_o are, respectively, the density of ambient air and the speed of sound propagating through it. x_o is the position where the point source locates, q is its source strength, and S is the cross-sectional area of the duct to be adopted. When a primary source of strength q_p and a secondary source of strength q_s are placed at x = 0 and x = l, respectively. The resulting acoustic pressure is:

$$p(x) = \frac{\rho_o c_o q_p e^{-jk|x|}}{2S} + \frac{\rho_o c_o q_s e^{-jk|x-x_l|}}{2S} \tag{2}$$

As shown in Fig.1, when the strength of the two sources has the relationship of $q_s = -q_p e^{-jkl}$, the acoustic field downstream the secondary source must be a silence zone. Using the Fourier transform in real-time domain on the strength relationship as above between two sources can obtain:

$$q_s(t) = -q_p\left(t - \frac{l}{c_o}\right) \tag{3}$$

In order to eliminate the acoustic pressure downstream the secondary source, eqn(3) tells us that the secondary source must be the same strength but l/c_o time delay as that of the primary source. Regarding the acoustic field upstream the secondary source, should be an acoustic feedback field to the primary source. In order to greatly reduce the inefficient influence of acoustic feedback as described to the control effectiveness, two specially designed frameworks of passive type are used for the experiment required for this study.

From the text of neutral network[10], and some past studies[9-20], the neutral network has some special properties such as non-linearity, adaptivity, learning, memory and fault tolerance are included. Following Chou's thesis[21], this study adopts the back-propagation neutral network and its associated error algorithm as the required ones. Figs.2 shows the description to the back- propagation neutral network to be adopted. By the similar manner of derivation as that of Chou's study[21], the output u_j of j-th neuron in the output layer as shown in Fig.2 can be expressed as:

$$u_j = f\left(net_j\right) \tag{4}$$

In eqn(4), f is the activation function of neuron, which is a hyperbolic function in this study, $net_j = \sum_h \left(w_{hj}.hid_h\right) + \theta_j$ is the input of j-th neuron, w_{hj} and θ_j are the associated weighting parameter and bias. Furthermore, $hid_h = f\left(net_h\right)$ is the output of the h-th neuron, $net_h = \sum_h \left(w_{ih}.x_i\right) + \theta_h$ is its corresponding input, and w_{ih} , θ_j are the associated weighting parameter and bias. Generally, the real output u_j of a neutral network is always not coincident with its desired output t_j, the error function E between them can be defined as:

$$E = \frac{1}{2}\sum_j \left(t_j - u_j\right)^2 \tag{5}$$

Using the steepest gradient method for the error back-propagation algorithm to minimize eqn(5), and after some complicate manipulations, either the modified weighting coefficients or the associated bias at any instant (t+1) from the h-th neuron in hidden layer to the j-th neuron in the output layer can be expressed in terms of those one at earlier time t as :

$$w_{hj}\left(t+1\right) = w_{hj}\left(t\right) + \eta\delta_j hid_h \tag{6}$$

$$w_{ih}\left(t+1\right) = w_{ih}\left(t\right) + \eta\delta_h x \tag{7}$$

$$\theta_j\left(t+1\right) = \theta_j\left(t\right) - \eta\delta_j \tag{8}$$

$$\theta_h\left(t+1\right) = \theta_h\left(t\right) - \eta\delta_h \tag{9}$$

η is the learning rate of the neural network, $\delta_{j,h} = \left(t_{j,h} - u_{j,h}\right)\left(1 + u_{j,h}\right)\left(1 - u_{j,h}\right)$.

To get better control effectiveness, a framework for special learning, which is shown in Fig.3, can on-line and in real time modify the weighting coefficients of the adopted back-propagation neutral network. Upon the discussion as above, we can apply the back-propagation neutral network with special learning framework to the active noise control in duct. Fig.4 shows the corresponding sketch.

EXPERIMENT and RESULTS

This study is a new try to combine a back-propagation neutral network with its associated error algorithm for the active acoustic control in a duct. Fig.5 shows the corresponding setup for the active-neutral network control experiment. In order to eliminate the influence by the acoustic feedback from the secondary source on the reference microphone downstream the primary source, a passive device, also shown in Fig.5, is adopted. The equipments involved in Fig.5 are all the same as that for Chou's study[21], the illustration for them in detail are not discussed in this paper. After some trial and error for pure-tone sound, it is decisively to select the optimum values of learning rate $\eta = 0.01$, of initial weighting coefficient $w_{hj}(0) = w_{ih}(0) \ = 0.01$, of initial bias $\theta_j(0) = \theta_h(0) = 0.01$, and of the respective amount $i = 6, h = 3, j = 6$ of neurons, in input, hidden and output layers for the neutral network control system adopted in experiment. Upon the equipment arrangement as shown in Fig.5, we can measure both the residual acoustic pressure and associated power downstream the secondary source when the experiment is making in progress at ten frequencies from 100 to 900 Hz. The corresponding attenuation at ten frequencies as measured are 57.4, 52.7, 54.9, 47.2, 46.5, 40.6, 40.8, 43.4, 47.6, 44.8, 36.8, 38.1 dB in residual pressure, and 40, 48, 46.5, 41.6, 44.5 33.0, 43.1, 34.5, 41.7, 37.5, 30.9, 35.9 dB in residual power. Figs. 6,7, respectively, show the residual acoustic pressures before and after active control at 100 and 800 Hz. Otherwise for dual-tone sound case, changing the respective amount of neurons, in input, hidden and output layers of the adopted back-propagation neutral network to be $i = 15, \quad h = 15 \quad , j = 15$ for getting better control effectiveness, and keeping the remaining unchanged, can make the experiment in progress at four dual- tone frequencies of 300-315, 300-350, 360-400, and 450-550 Hz. The attenuation of residual acoustic pressure at the above four frequencies are 19.6, 23.7, 27.4, and 27.7 dB.

CONCLUSIONS

From the results as measured in experiment for pure-tone sound, the back-propagation neutral network system with optimum parameters and an appropriate amounts of neurons for the active control of sound transmission in duct can provide attenuation of both residual acoustic pressure and the associated power by more than 50, 40 dB at low frequency and 37, 30dB at higher frequency. Regarding the dual-tone sound, optimum parameters of the system involved are still the same, but must change the amount of neuron to be more. The attenuation in residual pressure has the greatest value of 27.7 dB at the highest dual-tone of 450-550 Hz, and lowest value of 19.6 dB at the lowest dual-tone of 300-315 Hz.

ILLUSTRATIONS

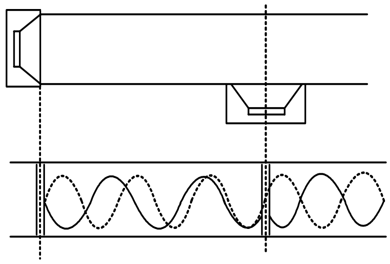

Fig.1 The acoustic interference between the fields produced by a primary and a secondary sources.

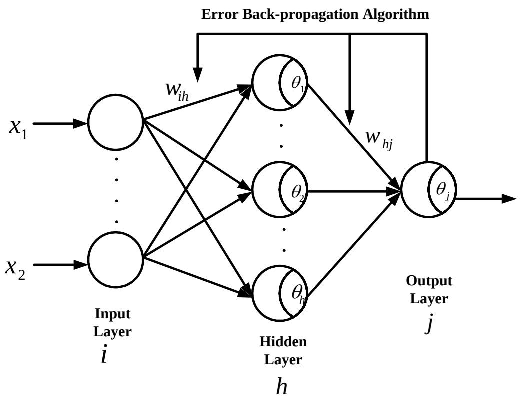

Fig. 2 Block diagram for an Error Back-propagation Neural Network

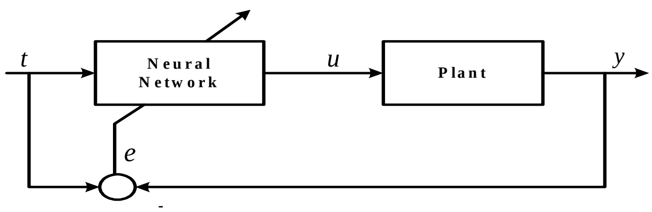

Fig.3 The block diagram of a special learning framework

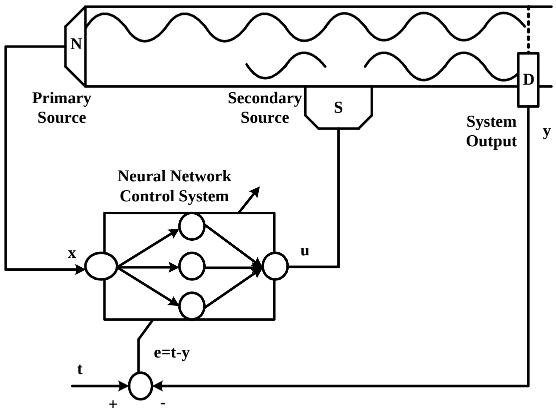

Fig.4 The sketch of a back-propagation neutral network with special learning

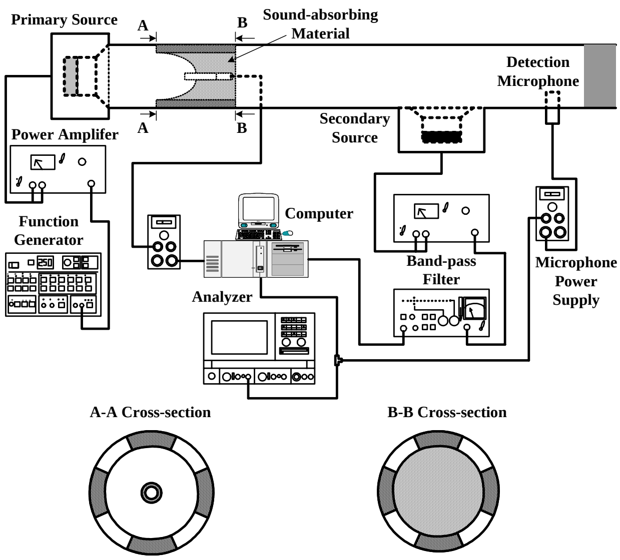

Fig.5 Setup of all equipments in the neutral network control experiment.

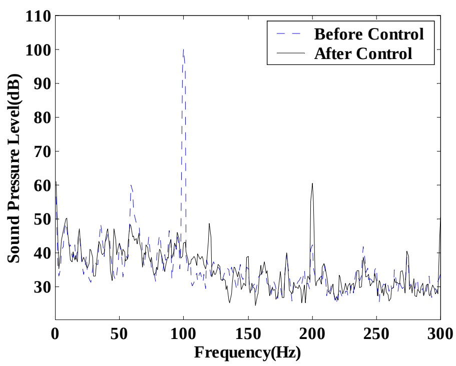

Fig. 6 The residual sound pressures at 100Hz before and after active control.

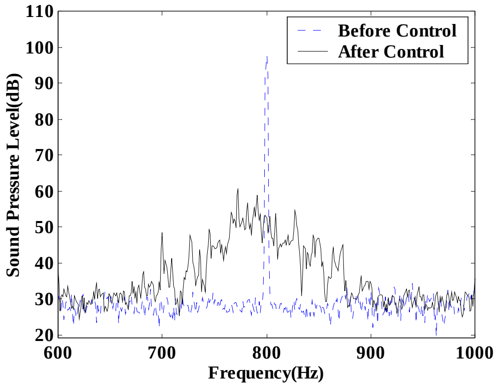

Fig.7 The residual sound pressures at 800Hz before and after active control.

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