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A Simplified Prediction Method for Environmental Noises Using Neural Network Model

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ABSTRACT

As is well known, the prediction of environmental noises is essential in the field of noise evaluation and/or regulation problems. In the actual living environment, however, when predicting the response probability distribution function of complicated working environmental systems, it is very difficult to evaluate the whole image of the acoustic characteristics of complicated acoustic systems by using the structural methods of traditional types. In this paper, we propose a simplified prediction method for the output response of complicated acoustic systems by introducing a neural network model for correcting a linear model. Finally, the effectiveness of the proposed method has been experimentally confirmed by applying it to actual room acoustic noise data.

Keywords: Prediction of Environmental Noises, Neural Network Model, Stochastic Response, Room Acoustic Systems

1. INTRODUCTION

As is well known, the prediction of environmental noises is important in the field of noise evaluation and regulation problems. In actual living environments, however, it is very difficult to predict the stochastic response and/or evaluate the transmission characteristics of complicated sound environmental systems, e.g., sound-bridge type sound insulation systems, non-parallel double-wall type sound insulation systems, etc., by using only conventional methods of the structural type like the wave equation, S.E.A. method and the acoustic image method and so on [1-3].

In this case, we can employ the regression analysis method between the input and output fluctuations, especially from the viewpoint of functional approach. The well-known regression analysis method, however, is constructed under the assumption of linear regression relationship based on Gaussian property and the usual least squares error criterion [4].

In this paper, a new method for the stochastic output response is proposed by introducing a linear model and its correction term based on neural networks [5]. Finally, the effectiveness of the proposed method has been experimentally confirmed by applying it to actual room acoustic noise data.

2. OUTPUT RESPONSE FOR ROOM ACOUSTIC SYSTEMS

Let us consider a typical room acoustic system, as shown in Fig.1. An acoustic signal of a sound fluctuation is measured at a receiving point in a room after propagating complicatedly through the surrounding walls, corridors and ceilings. Let us define the input sound pressure signal at the n-th octave (or one-third octave) band as $P_i^{(n)}(t)$, and the output sound pressure signal at the n-th octave (or one-third octave) band as $P_o^{(n)}(t)$. Based on the frequency transfer coefficient a_n, the output sound pressure $P_o^{(n)}(t)$ at the n-th frequency band is expressed by the linear combination with the input sound pressure $P_i^{(n)}(t)$ at the n-th frequency band, as follows :

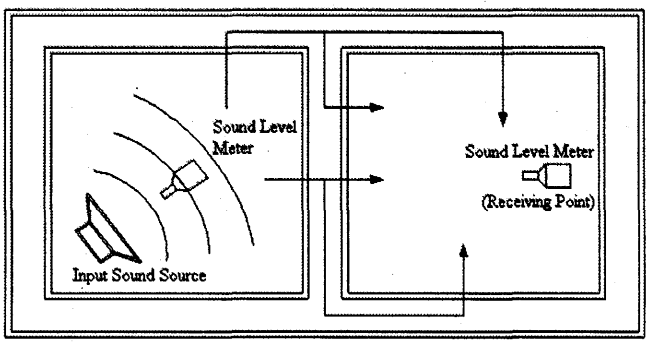

Fig.1 Typical room acoustic system.

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$$P_0^{(n)}(t) = a_n P_i^{(n)}(t)\,. \tag{1}$$

The output sound energy $E_o^{(n)}(t)$ at the n-th frequency band can be given as

$$E_0^{(n)}(t) = \overline{\{P_0^{(n)}(t)\}^2} = \overline{\{a_n P_i^{(n)}(t)\}^2}$$

$$= a_n^{\,2}\,\overline{\{P_i^{(n)}(t)\}^2} = a_n^{\,2} E_i^{(n)}(t)\,, \tag{2}$$

where $\overline{*}$ denotes the time averaging operation during the time constant of a sound level meter (i.e., 0.125 second for "First" or 1 second for "Slow"). Moreover, the following formula has been used :

$$E_i^{(n)}(t) = \overline{\{P_i^{(n)}(t)\}^2}\,. \tag{3}$$

Therefore, the over-all sound energy can be given as

$$E_0(t) = \sum_n E_0^{(n)}(t) = \sum_n a_n^{\,2} E_i^{(n)}(t)$$

$$= \sum_n b_n E_i^{(n)}(t), \quad (b_n \equiv a_n^2). \tag{4}$$

It is noticeable that Eq.(4) is a well-known formula in the field of acoustics [6]. For simplicity of experimental procedures, the energy frequency characteristic b_n can be expressed by introducing the averaged characteristic b_0 and the fluctuation component Δb_n, as follows :

$$b_n = b_0 + \Delta b_n\,. \tag{5}$$

By substituting Eq.(5) into Eq.(4), the following formula can be obtained :

$$E_0(t) = \sum_n (b_0 + \Delta b_n) E_i^{(n)}(t)$$

$$= b_0 \sum_n E_i^{(n)}(t) + \sum_n \Delta b_n E_i^{(n)}(t)\,. \tag{6}$$

In the second term of Eq.(6), the frequency energy components $E_i^{(1)}, E_i^{(2)}, \cdots$ and $E_i^{(n)}$ fluctuate randomly according to the non-stationary random input source. By describing the over-all input energy as $E_i(t)$, the second term of Eq.(6) can be rewritten as

$$\sum_n \Delta b_n E_i^{(n)}(t) = \Delta b_1 E_i^{(1)}(t) + \Delta b_2 E_i^{(2)}(t) + \cdots + \Delta b_n E_i^{(n)}(t)$$

$$= \Delta b_1 c_1(t) E_i(t) + \Delta b_2 c_2(t) E_i(t) + \cdots + \Delta b_n c_n(t) E_i(t)$$

$$= E_i(t)\{\Delta b_1 c_1(t) + \Delta b_2 c_2(t) + \cdots + \Delta b_n c_n(t)\}\,, \tag{7}$$

where $c_1(t)$, $c_2(t)$, $\cdots$ and $c_n(t)$ are the energy contribution rates at each frequency band. Thus, the second term of Eq.(6) can be generally expressed in an arbitrary non-linear function, as follows :

$$\sum_n \Delta b_n E_i^{(n)}(t) = \varepsilon\{E_i(t)\}\,. \tag{8}$$

Therefore, by substituting Eq.(8) into Eq.(6), the following equation can be obtained :

$$E_0(t) = b_0 E_i(t) + \varepsilon\{E_i(t)\}\,. \tag{9}$$

The second term of Eq.(9) means the correction term of the estimated value derived from the representative over-all energy characteristic b_0. By using Eq.(9) after the identification of $\hat{b}_0$ and $\hat{\varepsilon}\{\bullet\}$ from the learning data, we can predict the output response $\hat{E}_o(t)$ for the input signal $E_i(t)$, as follows :

$$\hat{E}_0(t) = \hat{b}_0 E_i(t) + \hat{\varepsilon}\{E_i(t)\}\,. \tag{10}$$

3. LEARNING THE CORRECTION TERM USING NEURAL NETWORK

The multi-layered neural network for learning the correction term $\varepsilon\{E_i(t)\}$ can be used as the learning algorithm, since it is very effective to model various non-linear properties. Now, we introduce a three-layered neural network, as shown in Fig.2. The number of input and output units is respectively one. The number of hidden units should be set according to the non-linear property of correction term. The functions of input and output units are linear. By taking account of the non-linearity of correction term, the function $F(\bullet)$ of hidden units is given by the sigmoid function with the slope β :

$$F(x) = \frac{2}{1+\exp(-\beta x)} - 1\,. \tag{11}$$

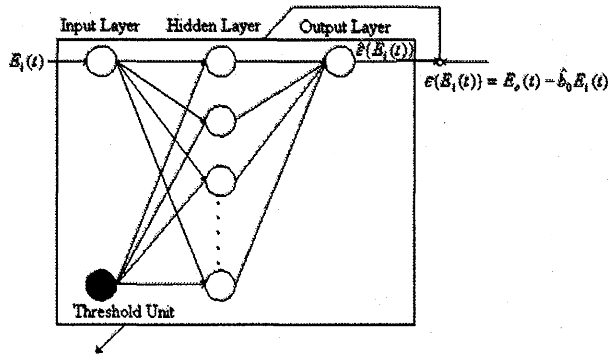

Fig.2 Neural network for learning the correction term.

This neural network is trained by the back-propagation (BP) algorithm [5].

4. EXPERIMENTAL CONSIDERATION

In order to confirm the effectiveness of the proposed method, let us apply it to a prediction problem of output response of an actual room in living environment. Fig.3 shows the arrangement of experimental apparatus. In the acoustic experiment, the traffic noise has been excited as an input stochastic signal in a corridor and an output stochastic signal has been measured in the neighboring room. The simultaneous data for input and output sound pressure signals have been measured at a sampling frequency 10 kHz. The total number of input and output data is 600000 respectively. These data have been transformed into the sound energy fluctuations. The total number of input and output sound energy data is 480. The data up to 240 has been used for identifying the correction term. The energy frequency characteristic b_0 has been obtained in advance by using an over-all white noise ($b_0 = 6.40 \times 10^{-4}$).

Fig.4 shows the estimated curve of the correction term by using three-layered neural network. Here, the number of hidden units has been set as four. The slope β of sigmoid function was 1.1 and the learning coefficient in BP algorithm was 0.02. The learning iterations were fixed to 10000. Fig.5 shows the estimated result for the learning data on an energy scale by using the proposed method. The estimated result on a decibel scale matched to the noise evaluation is shown in Fig.6. Here, $L_i(t)$ and $L_o(t)$ denote respectively the input and output sound level fluctuations on a decibel scale.

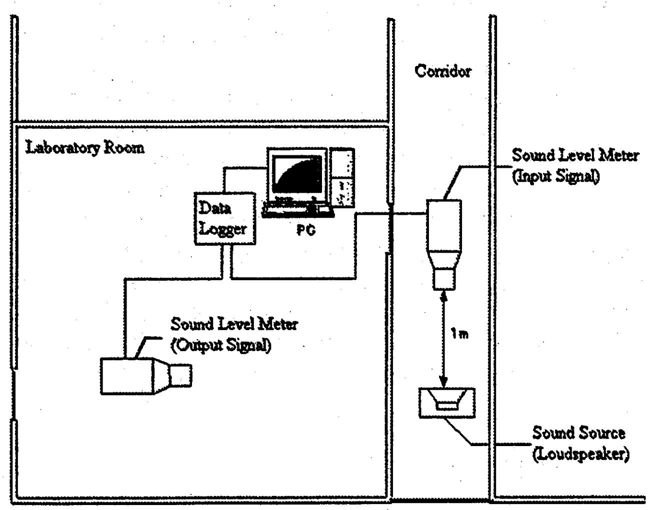

Fig.3 Arrangement of experimental apparatus.

Fig.7 shows the predicted result on an energy scale by using the proposed method. The predicted result on a decibel scale matched to the noise evaluation is shown in Fig.8. The estimation errors on both energy and decibel scales are shown in Table 1. Table 2 shows the prediction errors on both energy and decibel scales. The results using the conventional method (i.e., the linear regression analysis on an energy scale) are also shown in these tables. From these results, the results using the proposed method are better than the results using the conventional method.

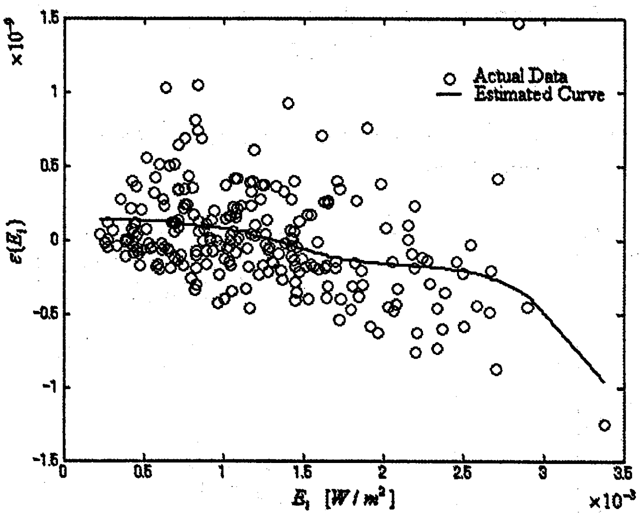

Fig.4 The estimated curve for the correction term.

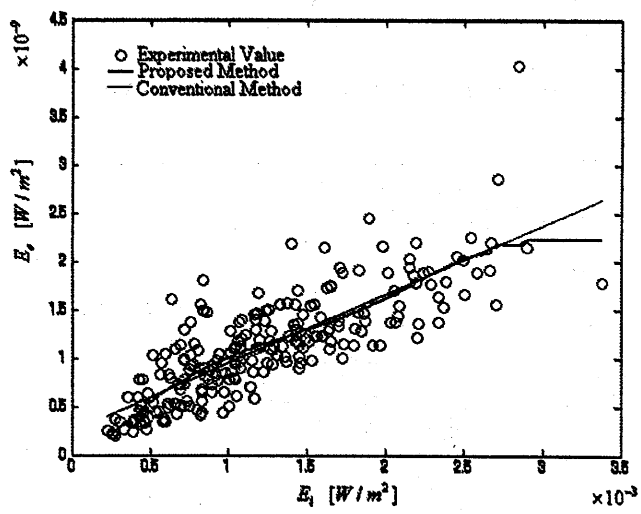

Fig.5 The estimated result for the learning data on an energy scale.

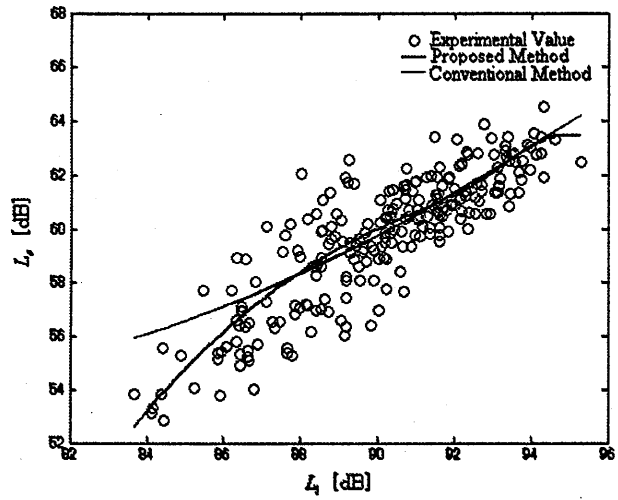

Fig.6 The estimated result for the learning data on a decibel scale.

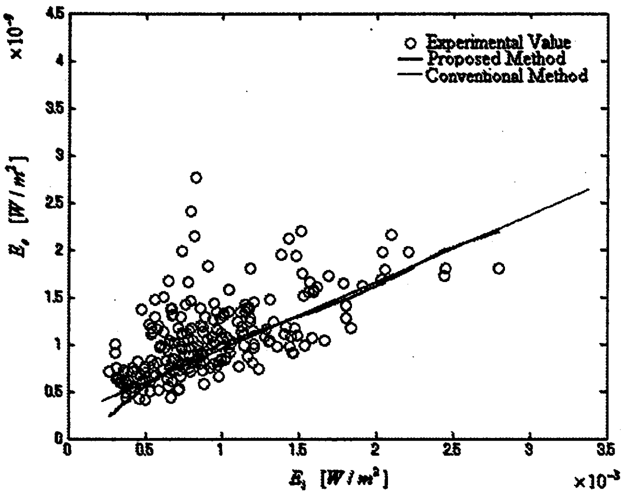

Fig.7 The predicted result on an energy scale.

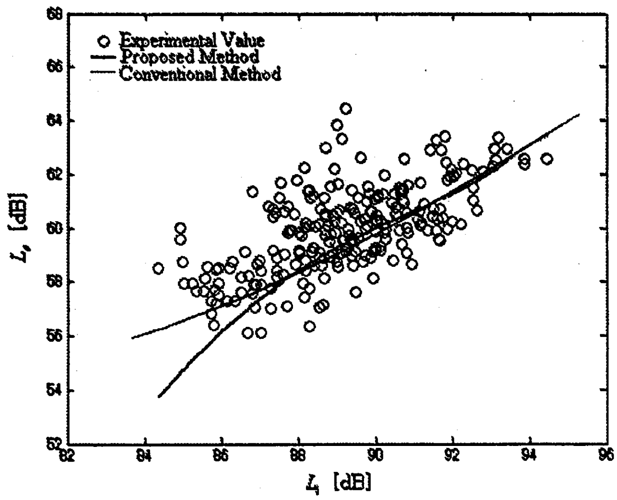

Fig.8 The predicted result on a decibel scale.

Table 1 The estimation errors on both energy and decibel scales.

	R.m.s. Error on Energy Scale $[W/m^2]$	R.m.s. Error on Decibel Scale $[dB]$
Conventional Method	3.15×10^{-7}	1.33
Proposed Method	3.07×10^{-7}	1.26

Table 2 The prediction errors on both energy and decibel scales.

	R.m.s. Error on Energy Scale $[W/m^2]$	R.m.s. Error on Decibel Scale $[dB]$
Conventional Method	4.43×10^{-7}	1.89
Proposed Method	3.66×10^{-7}	1.60

5. CONCLUSION

The prediction of environmental noises is important in the field of noise evaluation and regulation problems. In actual living environments, however, it is very difficult to predict the stochastic response and/or evaluate the transmission characteristics of complicated sound environmental systems. In this case, we can employ the regression analysis method between the input and output fluctuations, especially from the viewpoint of functional approach. The well-known regression analysis method, however, is constructed under the assumption of linear regression curve based on Gaussian property and the usual least squares error criterion.

In this paper, a new prediction method for the stochastic output response has been proposed by introducing a linear model and its correction term based on neural networks. Finally, the effectiveness of the proposed method has been experimentally confirmed by applying it to actual room acoustic noise data. This research is still in an early stage and the work reported here has been focused on some methodological aspects. There remain future problems in applying the proposed prediction method to other actual engineering situations.

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