

Objective Evaluation of Interior Sound Quality in Passenger Cars Using Artificial Neural Networks

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ABSTRACT

In this research, the interior noise of a passenger car was measured, and the sound quality metrics including sound pressure level, loudness, sharpness, and roughness were calculated. An artificial neural network was designed to successfully apply on automotive interior noise as well as numerous different fields of technology which aim to overcome difficulties of experimentations and save cost, time and workforce. Sound pressure level, loudness, sharpness, and roughness were estimated by using the artificial neural network designed by using the experiment values. The predicted values and experiment results are compared. The comparison results show that the realized artificial intelligence model is an appropriate model to estimate the sound quality of the automotive interior noise. The reliability value is calculated as 0.9995 by using statistical analysis.

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INTRODUCTION

In recent years, the interior noise of automobile has been becoming an important factor in the customer perception of the overall quality of automobile [1,2,3,4,5,6]. Especially, sound quality has been becoming a major concern of acoustic problem in vehicles [7,8,9,10,11,12,13]. A large research effort related to sound quality of vehicle interior noise has been conducted, and human perceptive factors that lead to positive emotional states have been taken into account [14, 15]. Subjective and objective evaluations are both evaluation methods used for sound quality analysis [16]. Numerous psychoacoustic indices including A-weighted sound pressure level (SPL), loudness, sharpness, roughness, etc. have been used to evaluate interior noise of automobile [17].

In order to reduce the interior noise of automobile, numerous measures including active and passive measures have been taken for vehicle manufactures [18,19,20]. More and more quiet vehicles are produced. However, the acoustic performance of the interior environment of vehicle can be perceived by drivers and passengers. Thus, the sound quality of automobile becomes more and more important.

Active noise control methods have been applied to sound quality analysis. Leopoldo P. R. de Oliveira, et al. presented a novel adaptive control scheme for harmonic sound quality

control with NEX-LMS [7], and the effect of a feedback controller on the sound quality of a vehicle mockup excited with engine noise was numerically and experimentally evaluated [21]. Sen M. Kuo, et al. [22] presented several broadband active sound quality control algorithms based on delayless frequency-domain techniques and subband adaptive filters, and the algorithm was also simulated in applications requiring high-order adaptive filters. Also, an active sound quality control (ASQC) system was developed based on the active noise equalization (ANE) technique [23]. A. Gonzalez, et al. [24] evaluated the ability of active noise control systems to achieve a more pleasant sound throughout sound quality analysis of a real multi-channel active noise controller.

Not only the sound quality of the stationary noise but also the sound quality of nonstationary noise have been investigated. Door closing noise, accelerating noise, decelerating noise, etc. are all nonstationary noise. Y. S. Wang [25] presented a new method based on the discrete wavelet transform for sound quality estimation of nonstationary vehicle noise. Door closing sound quality is one of the most important indices for vehicle acoustic performance. Vehicle door closing sound quality was analyzed in the low frequency range from 0 to 300 Hz based on a new CAE tool developed using finite element and

boundary element methods [26]. Kuwano, Sonoko, et al. [27] investigated the relationship between the subjective impression of the door sounds and the metal image of the passenger car examined in an experiment using German and Japanese participants. Haeseung Lee, et al. [28] built a model of door slam noise index using sound quality metrics. Etienne Parizet, et al. [29] also analyzed the perception of the noise coming from a car's door closure. Farokh Kavarana, et al. [30] developed an efficient approach to improve the sound quality of vehicle acceleration with an NVH simulator.

Artificial neural network (ANN) also has been used in sound quality analysis. Sang-Kwon Lee, et al. [31] investigated the relationship between the booming index and sound metric using an artificial neural network, and the objective evaluation of the interior sound quality in passenger cars during acceleration was presented [32]. Y. S. Wang, et al. [6] created a new concept for sound quality prediction, the so-called wavelet pre-processing neural network model by combining the techniques of wavelet analysis and neural network classification. The hybrid neural networks were also used for sound quality analysis of automobiles [33].

In this research, a feed forward neural network was designed. The sound quality metrics including sound pressure level, loudness, sharpness, and roughness were calculated and predicted using the designed artificial neural network.

EXPERIMENT



Fig. 1. Artificial head placed at the front passenger seat

Binaural recordings of interior noise were made using an artificial head (B&K 4100 D type, Fig. 1) placed on front passenger seat. The artificial head was adjusted until both of the left and right microphones were in ear positions for an average male passenger. The interior noises of the passenger car with 4-cylinder gasoline engine were recorded every 10 km/h from 60 km/h to 130 km/h. The accessories such as air conditioning, audio, wipers, etc. were all turned off, and the windows were all closed. Therefore, the interior noise of the passenger car was basically composed of road noise, engine noise, wind noise, and exhaust noise.

The objective evaluation metrics including sound pressure level, loudness, sharpness, and roughness were calculated after the experiment.

DESIGN OF ARTIFICIAL NEURAL NETWORK

Artificial neural networks are computational systems developed to have computational abilities as intelligently generating, forming, and discovering new knowledge without any help as biological systems such as human brain using numerous interconnected artificial neurons. Neural networks are used to build complicated relationships between inputs and outputs or for a specific application such as prediction, pattern recognition, data compression, optimization, system modeling, identification, function approximation, or control [34]. Neural networks can also be used to deduce functions from observations. Every neuron of neural network is connected to others through direct communication link, and each connection is with an associated weight. The network with connections and weights is shown in Fig. 2. The output of the neural network can be written as

$$y = f(Wp + b) \quad (1)$$

where p is the input of the network, W is the weight, b is the bias, y is the output of the neural network, R is the number of elements in input vector, S is the number of neurons in layer, n means the neurons.

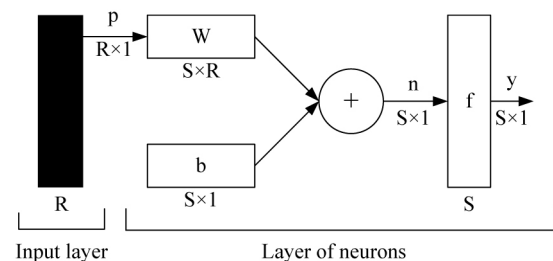


Fig. 2. Schematic diagram of neuron and its connections

The bias shown in Eq. (1) is an activation threshold added to the product of input data and the respective weighting factors. Several most commonly used transfer functions are logarithmic sigmoid, hyperbolic tangent sigmoid, and linear functions [35]. The input of transfer function can be acquired through weighted sum of all input plus the bias of neuron. It is concerned that the important characteristics of the transfer function is its differentiability because of its facilitating the training of the network throughout gradient-based training algorithms. The transfer function serves as a type of filter or gate that makes some signals move forward and stops the others as they propagate from the input to output. Therefore, the smaller the value of the output of the neuron is, the less its effect on the next neurons would be.

In order to design an ANN model, the neural network can be divided into two processes including training and test. The

neural network is trained to predict the output values which are relative to input data in training process. The training process is finished when the error reaches the tolerance value which is previously determined. Then, the network is tested to stop training or save training data, and it is also used to predict an output.

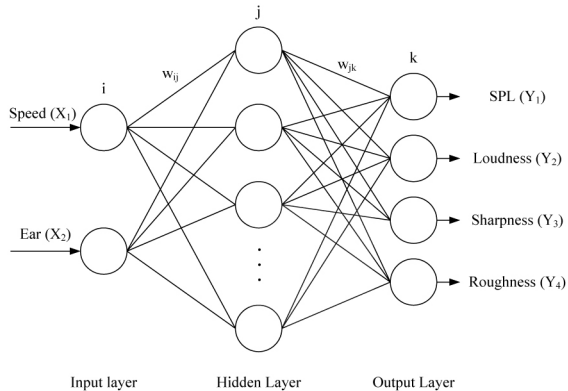


Fig. 3. Architecture of BP network

The error back propagation (BP), one of the most popular techniques, is commonly used in the field of ANN. It is also a kind of supervised learning neural network. BP consists of two processes of feed forward and back propagation. In feed forward process, knowledge is generated from the input layer to the output layer. The output value acquired in feed forward process is compared with the target value, and the difference between the output and target values is calculated and compared with previously determined difference tolerance in propagation process. The difference value is propagated backward to update the links in the input layer [36]. The BP training algorithm is a gradient descent algorithm, and the training of the network is stopped when the tested values of mean square error (MSE) stop decreasing. The MSE can be expressed as

$$E = \frac{1}{n} \sum_{i=1}^n (T_i - Y_i)^2 \quad (2)$$

where T is the target value, Y is the output value of the neural network, n is the number of the output data.

A model of BP is shown in Fig. 3. The BP model is composed of three layers including input layer, hidden layer, and output layer. Every two nodes between input layer and hidden layer, or between hidden layer and output layer are directly connected, and the connections are called links. A weighted value is included in each link to present the relationship between two nodes.

Assume that two input neurons, m hidden neurons, and four output neurons are included in the BP network model, we can infer a training process to update the weighted values. The outputs of the neurons in the hidden layer can be expressed as

$$y_j = f_1(w_{1j}X_1 + w_{2j}X_2) \quad j = 1, 2, \dots, m \quad (3)$$

$$f_1(x) = \frac{2}{1 - e^{-2x}} - 1 \quad (4)$$

where y_j is the output of the j th neuron of the hidden layer, f_1 is the transfer function of the hidden layer, and it is sigmoid function, w_{ij} is the weighted value between the i th neuron in the input layer and j th neuron in the hidden layer.

The outputs of the output layers are given by:

$$Y_k = f_2\left(\sum_{j=1}^m w_{jk}y_j\right) \quad j = 1, 2, \dots, m; k = 1, 2, 3, 4 \quad (5)$$

where f_2 is the transfer function in the output layer, it is usually a linear function, w_{jk} is the weighted value between the j th neuron in the hidden layer and k th neuron in the output layer.

APPLICATION OF FEED FORWARD NETWORK

In this study, a BP network with an input layer, a hidden layer, and an output layer was used, and it is shown in Fig. 3. This feed forward network was used for predicting the objective metrics of sound quality for a passenger car depending on the numerous input and output elements relative to sound quality. All the data were acquired from the interior noise experiment, and they were divided into training and test data sets. The experimental data consisted of 160 values. The network was trained and validated by using 70% and 15% of the experimental data, respectively. The prediction results were compared with 15% of the experimental data which were not used in the model development. Therefore, the accuracy of the presented model was tested against 45 independent data points. The training of the network was performed by back propagation algorithm. As the hidden layers were composed of non-linear processing elements as neurons, Tangent-Sigmoid (TANSIG) transfer function was applied in this research. Meanwhile, a trial-and-error approach has been used to minimize the error for the purpose of determining the optimal combination of number of hidden layers. At the beginning of the training process, the weights were prepared for the first use. The learning ratio was set as 0.01.

The linking weights between input layer and hidden layer, hidden layer and output layer were randomly prepared for the first time at the beginning of the training stage. The BP network was trained until it reached the mean square errors (MSE) which were defined as the differences between network outputs and target outputs. The MSE was set to 1×10^{-5} . The training data are learned repeatedly if the MSE is larger than 1×10^{-5} , and the training process will stop until the MSE reaches the desired tolerance. Additionally, the