Vehicle Interior Sound Quality Prediction Based on Back Propagation Neural Network

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Abstract

Conduct interior vehicle acoustic quality evaluation to improve automobile comfort is very important significance. This paper introduces the BP neural network application in the vehicle acoustic quality prediction, and set up a sound quality of prediction model with BP network. The network was trained using variable learning rate back propagation algorithm. Interior vehicle sound quality was analysed and predicted by using trained neural network model, and then prediction results are analysed. Simulation results indicated that neural network prediction results are close to subjective evaluation score, and has little error and good prediction or generalization ability in the prediction of sound quality.

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Keywords: vehicle; sound quality; back propagation neural network; prediction; model

1. Introduction

Subjective evaluation of sound quality is the use of psychological methods to research sound quality issue which involves many contents, such as the preparation before the test, the choice of test methods and the analysis of test results. Subjective evaluation of sound quality needs large costs and much more time and its consistency and reproducibility is poor. The result of subjective evaluation test data can not directly describe that the sound quality in other similar condition is good or bad. Setting up an objective model of sound quality, which use equipment to measure and calculate the objective parameters of sound and is based on psychoacoustic parameters, is one of the hot research topics. Objective evaluation using a model of sound quality can significantly improve the evaluation efficiency and reduce evaluation costs, which have a positive effect on active noise control.
2. Sound quality

In 2006s, Wang Deng-feng et al.[1] acquired sixteen noise samples under steady-state conditions from different passenger cars. Subjective evaluation test was carried out by using grading score and paired comparison, and objective parameters, such as loudness, roughness and sharpness were computed. The result of subjective evaluation has been shown in Table 1. Using SPSS software for statistical analysis and multi-dimensional regression analysis, the correlation between subjective evaluation results of vehicle interior sound quality and psychoacoustic parameters had been acquired which was shown in Table 2. Finally, the multi-dimensional linear regression model of car interior sound quality which related to two input psycho-acoustical parameters: loudness and sharpness were provided.

| No. | score | Loud-ness (sone) | Sharp-ness (acum) | Fluctuation strength (vacil) | Rough-ness (asper) | dB(L) | dB(A) | dB(B) |
|-----|-------|-----------------|------------------|----------------------------|-------------------|-------|-------|-------|
| 1   | 9.32  | 41.22           | 0.9641           | 0.4744                     | 1.0811            | 91.2  | 72.7  | 85.5  |
| 2   | 3.59  | 30.15           | 0.8703           | 0.2078                     | 0.4857            | 103.1 | 63.0  | 84.3  |
| 3   | 7.50  | 33.23           | 0.9809           | 0.5707                     | 0.9728            | 90.3  | 66.4  | 80.9  |
| 4   | 13.27 | 54.29           | 1.0781           | 0.2344                     | 1.5348            | 91.4  | 76.5  | 87.3  |
| 5   | 12.82 | 52.85           | 1.0706           | 0.3483                     | 1.2736            | 92.8  | 75.9  | 87.6  |
| 6   | 14.91 | 49.40           | 1.3116           | 0.2391                     | 2.0941            | 86.0  | 73.4  | 81.7  |
| 7   | 5.55  | 17.41           | 0.9546           | 0.3414                     | 0.4719            | 81.5  | 57.8  | 70.7  |
| 8   | 13.09 | 53.06           | 1.0326           | 0.1722                     | 1.4339            | 92.1  | 75.4  | 87.2  |
| 9   | 5.99  | 22.30           | 0.9863           | 0.3736                     | 0.5467            | 74.0  | 55.8  | 67.3  |
| 10  | 8.24  | 39.67           | 0.9651           | 0.4896                     | 0.8231            | 85.6  | 75.3  | 81.0  |
| 11  | 10.86 | 38.86           | 1.1034           | 0.4186                     | 1.7631            | 95.9  | 66.5  | 85.0  |
| 12  | 2.79  | 24.02           | 0.7578           | 0.1892                     | 0.5762            | 92.9  | 60.8  | 79.6  |
| 13  | 9.97  | 36.50           | 1.0763           | 0.5309                     | 0.8019            | 74.3  | 65.1  | 68.4  |
| 14  | 7.02  | 29.89           | 0.9785           | 0.4563                     | 1.2820            | 92.6  | 58.7  | 78.1  |
| 15  | 4.63  | 18.30           | 0.9659           | 0.3007                     | 0.6931            | 69.6  | 59.4  | 63.9  |
| 16  | 11.38 | 51.89           | 1.2357           | 0.2038                     | 2.1764            | 99.9  | 71.7  | 86.5  |

Table 2: Reliability between subjective evaluation and psycho-acoustical parameters

| Correlation | Loudness | Sharpness | Fluctuation strength | Roughness | dB(L) | dB(A) | dB(B) |
|-------------|----------|-----------|----------------------|-----------|-------|-------|-------|
| 0.8996      | 0.8346   | -0.0818   | 0.8216               | 0.175     | 0.801 | 0.536 |
| 0.000       | 0.000    | 0.763     | 0.000                | 0.517     | 0.000 | 0.033 |

3. BP neural network

The back propagation algorithm based on multi-layer neural network was proposed and proved in 1986 by the research team of scientists led by Rumellhart and McCellland[2]. BP algorithm solves the multi-layer neural network learning problems, proved the computing capability of multi-layer neural network [3].

3.1. Basic structure and principle of BP neural network
BP neural network can learn and store a lot of input/output model mapping, without prior revealing the mathematical description of this equation [4, 5]. The topological structure of BP neural network has three layers including input layer, hidden layer and output layer. The network structure is shown in Figure 1, which one of circles represents artificial neuron, $i, j, n$, on behalf of neural network data pretreatment units, $f_i, f_j, f_n$, on behalf of the activation function, adder or multiplier; $V$ for the input layer and hidden layer connection weight vector or threshold vector; $W$ for the hidden layer and output level or threshold connection weight vector of vectors. No connection between the same layers, all one-way feed connection between different layers of interconnection. The main goal of back-propagation neural networks is mapping of input, i.e., vector $X$ into output, i.e., vector $Y$. The symbol of desired output of neural networks is $Z$.

![Neural network structure](image)

Figure1 Neural network structure

3.2. BP neural network algorithm

Its learning rule is the steepest descent method or delta rule, which weights and thresholds are adjusted by back-propagation of errors to guarantee that the minimum total error of the network. The application of the steepest descent method, thus, involves two phases: During the first phase the input is presented and propagated forward through the network to compute the output value for each unit. This output is then compared with the targets, resulting in an error signal for each output unit. The second phase involves a backward pass through the network (analogous to the initial forward pass) during which the error signal is passed to each unit in the network and the appropriate weight changes are made [2, 3]. Both iterative process until it reaches the convergence so far.

4. BP neural network model based on interior vehicle sound quality

BP neural network is mainly used in the regression (which can be fitted, data processing, analysis, forecast of things, control, etc.), classification and recognition (the type, pattern recognition), and other utilization, achieve great accomplishments [6~8]. In this paper, combined with the characteristics of interior noise, the sound quality inside the vehicle is predicted by neural network which have learning data and generalization ability.

4.1. Neural network model of vehicle interior sound quality

- Data normalization and data classification

In engineering applications, the application of BP neural network is a key factor in the input data selection and preparation of training samples. Data selection to be considered the main representative
sample, the sample excluded such contradictions, and then this data were normalized. It has already provided a built-normalized function in version of the MATLAB R2010, which can be easily to the engineering of dimensionless data whose value is mapped to [-1, 1] or [0, 1]. Data classification mainly concentrated in separating a set of input and target data into groups of vectors for training data, validating data and test data. Group of training data is used to train the structure of BP network; meanwhile, group of validating data is used to inspect BP network performance for avoiding training stop early if it attempts to overfit the training data [9]. And group of test data is used for an independent measure of how the network might be expected to perform on data which was not trained before.

- Determination of neural network structure

A three-layer network can approximate any continuous function, if BP neural network hidden lay can be set a random value according to the needs [10]. In this paper, a three-lay neural network was built which involving input layer, hidden layer (only a single hidden layer structure), output layer, after analysing the characteristics of vehicle interior sound quality. According to multi-dimensional correlation analysis, loudness and sharpness were selected as two input parameters in input layer. Output layer has only one output which indicates scores of the subjective evaluation results of vehicle interior sound quality. Because determining the number of hidden layer units had no scientific model and theory formula, we use trial and error to set the number of hidden layer unit 7. So topology structure of BP neural network is 2-7-1 as shown in figure 2.

4.2. Neural network training

A feed forward BP neural network was created using the function of newff in MATLAB R2010. Before training the BP neural network, parameters need to set and initialized. Accuracy of the training objectives is set as e-3. Adaptive variable learning rate BP algorithm is used in this article, which is indicated as traingdx in neural network toolbox in MATLAB. True gradient descent requires that infinitesimal steps be taken. The constant of proportionality is the learning rate in our procedure. The larger this constant, the larger the changes in the weights. For practical purposes we choose a learning rate that is as large as possible without leading to oscillation. One way to increase the learning rate without leading to oscillation is to modify the learning to include a correction term. This can be accomplished by the following rule:

\[
\eta(k+1) = \begin{cases} 
  k_w \eta(k) & E(k+1) < E(k) \quad k_w > 1 \\
  k_w \eta(k) & E(k+1) > E(k) \quad 0 < k_w < 1
\end{cases}
\]

Where \( k \) is the presentation number defined earlier, \( \eta \) is the learning rate, \( E \) is overall measure of the error.
5. Neural network prediction model and multi-dimensional regression model

In this paper, the 16 sets of multi-dimensional regression data were simulated in above neural network model. To increase the representativeness of the sample data, the original data were randomly divided into three groups, 50% of the data is taken as training data, 25% as validation data, and 25% as test data. The prediction results of neural network model are computed by using trained neural network model, and the analysis results of multi-dimensional regression model are given. Table 3 shows their correlation between neural network prediction results and multi-dimensional regression results. When neural network model predicts the training data samples which have been studied, the prediction of the data is closer to the subjective evaluation score and the absolute error is smaller, comparing to the results of multi-dimensional regression. Because of training neural networks model without using the validation data and test data, its prediction results is similar to the results of multi-dimensional regression, while the maximum absolute error of neural network model is still less than the results obtained from multi-dimensional regression.

The neural network prediction results are analyzed by regression tool as shown in figure 3. Dot diagram for the desired output or target output is the abscissa; the ordinate is the corresponding actual output of the neural network model. Dashed line is ideal curve which the assumptive output is equal to the desired output. Solid line is the regression analysis of above dot. Correlation coefficient and linear regression equation which correspond to the training data, validation data, test data, and 16 sets of data are given. It can be seen from Figure 3 that the value of correlation coefficient is high, and the regression curve of neural network model is close to the ideal curve, which indicates that the generalization ability of neural network model is better than multi-dimensional regression.

| No. | score | Groups of data | BP neural network | Multi-dimensional regression |
|-----|-------|----------------|-------------------|-----------------------------|
|     |       |                | Predict-ion result| Absolute error | Regression | Absolute error |
| 1   | 9.32  | Training data  | 9.10             | -0.22           | 8.80       | -0.52        |
| 2   | 3.59  | Training data  | 3.78             | 0.19            | 5.61       | 2.02         |
| 4   | 13.27 | Training data  | 13.28            | 0.01            | 12.59      | -0.68        |
| 5   | 12.82 | Training data  | 13.03            | 0.21            | 12.24      | -0.58        |
| 6   | 14.91 | Training data  | 14.61            | -0.30           | 14.71      | -0.20        |
| 7   | 5.55  | Training data  | 5.45             | -0.10           | 4.41       | -1.14        |
| 11  | 10.86 | Training data  | 10.83            | -0.03           | 10.16      | -0.70        |
| 14  | 7.02  | Training data  | 7.18             | 0.16            | 6.95       | -0.07        |
| 3   | 7.50  | Validation data| 7.74             | 0.24            | 7.58       | 0.08         |
| 8   | 13.09 | Validation data| 12.70            | -0.39           | 11.79      | -1.30        |
| 12  | 2.79  | Validation data| 3.13             | 0.34            | 3.08       | 0.29         |
| 16  | 11.38 | Validation data| 13.05            | 1.67            | 14.18      | 2.80         |
| 9   | 5.99  | Test data      | 6.66             | 0.67            | 5.69       | -0.30        |
| 10  | 8.24  | Test data      | 8.70             | 0.46            | 8.53       | 0.29         |
| 13  | 9.97  | Test data      | 9.63             | -0.34           | 9.39       | -0.58        |
| 15  | 4.63  | Test data      | 5.34             | 0.71            | 4.72       | 0.09         |

Table 3: Compare with BP neural network prediction results with multi-dimensional regression data
6. Conclusions

A vehicle interior sound quality prediction model is established based on BP neural network in this paper. Two psychoacoustic parameters, loudness and sharpness, are regarded as the input of the model, and subjective evaluation results of vehicle interior sound quality are taken as the output. Topological structure of the model is 2-7-1. Subjective evaluation scores of vehicle interior sound quality are predicted by using the model. A good agreement is indicated by comparing the BP neural network model prediction results of vehicle interior sound quality with the subjective evaluation results.

Comparing the neural network prediction results with multi-dimensional regression curve, the maximum absolute error of neural network prediction results is still less than the results obtained from multi-dimensional regression. Simulation results show that the neural network model has better ability than multi-dimensional regression in prediction of sound quality.

![Figure 3 Correlation between the output of neural network and the subjective rate](image)

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