

Active Noise Equalization of Vehicle Low Frequency Interior Distraction Level and its Optimization

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ABSTRACT

On the study of reducing the disturbance on driver's attention induced by low frequency vehicle interior stationary noise, a subjective evaluation is firstly carried out by means of rank rating method which introduces Distraction Level (DL) as evaluation index. A visual-finger response test is developed to help evaluating members better recognize the Distraction Level during the evaluation. A non-linear back propagation artificial neural network (BPANN) is then modeled for the prediction of subjective Distraction Level, in which linear sound pressure RMS amplitudes of five Critical Band Rates (CBRs) from 20 to 500Hz are selected as inputs of the model. These inputs comprise an input vector of BPANN. Furthermore, active noise equalization (ANE) on DL is realized based on Filtered-x Least Mean Square (FxLMS) algorithm that controls the gain coefficients of inputs of trained BPANN. Meanwhile, reference signal of this ANE system is extracted using proposed coherence-based method which chooses the frequency of reference signal according to the coherence level between interior noise and vehicle body vibration. Finally, after analyzing the relation among transfer function of input layer, hidden layer and output layer of modeled BPANN, the sensitivity of DL to the inputs is derived to bring forward a novel optimization methodology that is able to search the optimal gain coefficient vector using Sensitivity-based Gradient Optimization Method (SGOM) and thereby optimize the DL during ANE process. The result shows that DLs are improved significantly by applying this ANE system.

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INTRODUCTION

As vehicle interior noise level is getting increasingly lower, the study on sound quality that describes passenger's psychological effects and subjective perception induced by interior noise is paid more attention. Subjective evaluation is a popular methodology to quantify the sound quality [1,2], in which passenger's level of preference for the interior noise for instance, comfort, pleasant or annoyance, is usually selected as an evaluation index. Besides preferences, however, low frequency noise may also lead to disturbance on driver's attention [3,4], which increases the risk of accident. Distraction Level (DL) is introduced as evaluation index to quantify disturbance on driver's attention due to low frequency stationary noise and is the aim of subsequent active noise equalization (ANE) in this paper. Additionally, a newly developed visual-finger test was conducted to help subjects better recognize the disturbance caused by noise samples during subjective evaluation.

Sound quality reflects subjective perception and is not objectively measurable. There are, however, some objective metrics developed to describe sound features. The most common metric is frequency weighted sound pressure level (SPL) and additional psychoacoustic metrics [5,6] have been developed to describe subjective perception, such as Loudness, Sharpness and Roughness. Therefore a model that maps the objective and psychoacoustic metrics to the sound quality can be developed for the prediction of subjective merit. The most common model used is multiple linear regression [7,8], in which the objective metrics that exhibit the highest level of correlation to the subjective merit are included in a regression model. More recently, a non-linear approach based on artificial neural network (ANN) [8,9,10,11] has also been used. In this approach a set of objective or psychoacoustic metrics are fed into the ANN algorithm as inputs and the subjective merits are used as the output (or training target) set. Among various ANN models, the back propagation (BP) ANN model is widely applied successfully in sound quality applications. In this paper, BPANN was modeled for the prediction of DL, in which subjective merit of DL was set as output and linear sound pressure RMS amplitudes from five CBRs ranging from 20 to 500Hz were selected as inputs by correlation analysis between subjective DL and psychoacoustic metrics.

Active noise control (ANC) [12,13,14] systems based on the principle of superposition have evolved and developed in vehicle applications to cancel undesirable interior noise. However, for vehicle sound quality improvement, such as DL in this paper, it is desired to independently control some frequency components of the noise signal rather than have it totally canceled. This demand leads to an extension of the ANC concept to include noise equalization. In order to improve the vehicle interior DL, active noise equalization (ANE) system proposed by Kuo et al. [15,16,17], which used the Filtered-x Least Mean Square (FxLMS) algorithm was adopted in this work. The control of DL was realized by ANE system by adjusting the gain coefficients of five sound pressure amplitude inputs from modeled BPANN. During the ANE process the accuracy of reference signal is a key point to the system's efficiency. Generally, higher correlation between reference signal and primary signal leads to more efficient equalization control. In previous work, there were mainly two ways to extract the reference signal, one was directly using vibration signal on vehicle body [18,19], the other was based on engine speed from which reference frequency was derived and equaled to engine order frequency [20,21]. However, the former may suffer from disturbance of uncorrelated frequency components of vibration signal. In latter way, the selected engine order may not highly correlated with frequency of interior noise that needs to be controlled. Therefore, a coherence-based method that extracts the reference signal according to the coherence level between interior noise and vehicle body vibration is proposed in this paper.

According to ANE principle, various frequency components are controlled during equalization process. For DL controlling however, frequencies from various CBRs are used to characterize the human auditory range. Gain coefficients of metric level under each Critical Band Rate were equalized simultaneously. These gain coefficients compose a gain coefficient vector $\beta = [\beta_1, \beta_2, \dots, \beta_i]$. Sound quality can be optimized by finding an optimal gain coefficient vector β_{opt} during ANE process. In Ref. [22], Liu used an enumeration method to determine this optimal β_{opt} , which had disadvantage on iteration time when enumerating all the possible conditions. In this paper, a novel Sensitivity-based Gradient Optimization Method (SGOM) is proposed to search the optimal gain coefficient vector with less iteration time.

SUBJECTIVE EVALUATION OF DISTRACTION LEVEL

In order to evaluate the Distraction Level induced by interior stationary noise of a van, binaural noise signals of driver position from 41 different stationary running conditions (listed in Table 1 in Appendix) at various engine speed ranging from 800RPM to 2500RPM in neutral, fourth and fifth gear with different gain coefficients from 0 to 2 were recorded. The measurement was carried out on a chassis dynamometer inside a semi-anechoic chamber. Binaural noise signals were recorded by sensor, which mounted artificial head (Figure 1) with 48kHz sampling rate, which is one of the two sampling rate options of the sensor, and with 20-second duration.

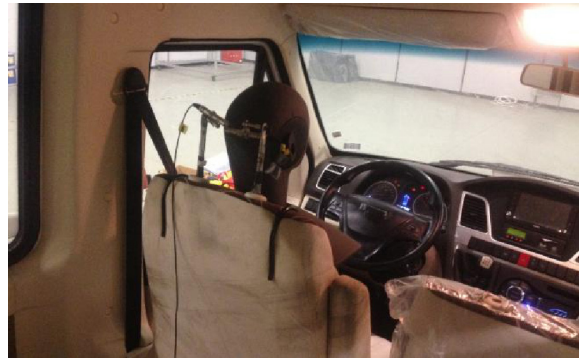


Figure 1. Measurement position of artificial head

As this work is focused on low frequency noise which is also the main contribution of engine orders, all the binaural signals are processed with 500Hz low pass filter as evaluation noise samples. A rating table is introduced (Table 2) to describe the Distraction Level, in which five levels from “Negligible Distraction” to “Very Severe Distraction” are defined. The merits are given with 0.5 intervals.

Table 2. Rating table of Distraction Level

Level	Very severe distraction	Severe distraction	Moderate distraction	Slight distraction	Negligible distraction
Merit	1	2	3	4	5

For better recognizing the Distraction Level, a visual-finger response test is introduced as a part of evaluation procedure. A sentence with prompt “Press ENTER when seeing this sentence” randomly pops up on the computer screen during the playback of each noise sample. The finger response time is shown after each test, which indirectly reflects the level of disturbance caused by noise samples. The response test is repeated for several times for each noise sample. Subjects give merit of each sample according to both subjective perception and finger response time.

Twenty subjects from university students (10 males and 10 females), aged 20 to 30, participate in the subjective evaluation. All of them have over one year driving experiences. The evaluation is performed with HEAD ACOUSTICS PEQ V playback system in a small quiet room. Visual-finger response test is repeated for three times during playback of each sample. Consistency test is performed to ensure the repeatability of merits given by each subject.

The results of subjective evaluation are showed in Figure 2 in which averaged merits from all the subjects of each sample are displayed. It is showed that merits of 29 samples, 70.7% of the total sample amount, are given below 3, which indicates low frequency vehicle interior noise has negative effect on driver's attention.

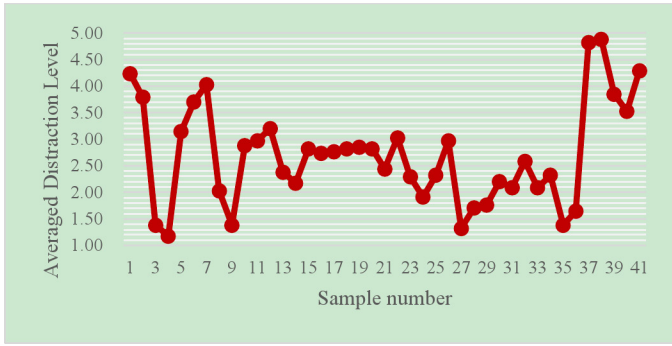


Figure 2. Averaged Distraction Levels of noise samples

ANN MODELING OF DISTRACTION LEVEL

For the prediction of Distraction Level from objective metrics, one needs to find the relationship between subjective Distraction Level and objective metrics, which in this case is complex and non-linear. Modeling approach of ANN is suitable for dealing with this kind of problem. A supervised feed-forward back propagation ANN (BPANN) with three-layer perceptron showed in Figure 3 is adopted in this paper to model the relationship between Distraction Level and objective metrics. x_j , y_i and O_k are nodes at input layer, hidden layer and output layer respectively. In BPANN, error calculated by comparing the output to the target is propagated backward through each layer from the output to the input of the network. The error at each node is used to adjust the weights and biases in an iteration way. The input $\{x_j\}$ is fed to the network and produces an output $\{O_k\}$ in the way shown as:

$$O_k = f_2 \left(\sum_{i=1}^m T_{ki} f_1 \left(\sum_{j=1}^n w_{ij} x_j - \theta_i \right) - \theta_k \right), (k=1, 2, \dots, l) \quad (1)$$

Where w_{ij} is the weight between j th input and i th hidden node, and T_{ki} is the weight between i th hidden and k th output node, θ_i and θ_k is the biases at hidden and output node respectively, $f_1(u)$ and $f_2(u)$ denote the transfer functions in hidden layer and output layer respectively. The transfer functions $f(u)$ in common use are pure linear (purelin), hyperbolic tangent (tansig), and log-sigmoid (logsig).

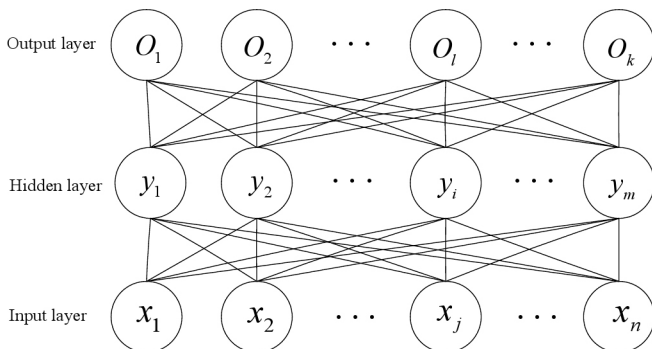


Figure 3. Three-layer BPANN

BPANN Inputs Determination

In order to train the BPANN, one needs a training dataset which consists of a known input vector and a target vector. In this case, the Distraction Levels from 41 samples are set as targets and the inputs are usually selected from the psychoacoustic metrics which are highly correlated with the targets. From an engineering point of view, however, it is not advisable to use psychoacoustic metrics directly as inputs for the subsequent ANE control, because the calculation process converting measured noise signals to psychoacoustic metrics may lower the efficiency of ANE system. In this case, correlation analysis results in Table 3 show that two psychoacoustic metrics, loudness (Zwicker) and sharpness, are highly correlated with subjective Distraction Level. These two metrics are both calculated in critical band which characterizes the auditory features of human by converting frequency scale into Bark scale. Zwicker loudness is calculated as:

Table 3. Correlation Coefficients between psychoacoustic metrics and Distractive Level

Psychoacoustic metrics	Loudness (Sone)	Sharpness (Acum)	Roughness (Asper)	Fluctuation strength (Vacil)	Tonality (Tu)
Correlation coefficient	-0.927	-0.830	-0.432	-0.500	-0.145

$$N = \int_1^{24 \text{ Bark}} N'(z) dz \quad (2)$$

where N is the total loudness in sone, and z is the Critical Band Rate in Bark. The specific loudness N' of a sound is defined as:

$$N' = N'_0 \left(\frac{E_{iq}}{sE_0} \right)^k \left[\left(1 + \frac{sE}{E_{iq}} \right)^k - 1 \right] \quad (3)$$

Where N'_0 (in sone/Bark) is the referenced specific loudness, E is the sound intensity in each critical band, E_{iq} and E_0 are the sound intensities under the conditions of quiet ambient and the reference sound intensity of $E_0 = 10^{-12}$ W/m² respectively. S and k are the coefficients.

According to Equation (3), the specific loudness N' can be expressed as a function of sound intensity E in critical band. Meanwhile, the sound intensity E is expressed by measured sound pressure as shown as:

$$E = \frac{P^2}{2\rho v} \quad (4)$$

Where P denotes the sound pressure amplitude of noise sample, ρ is the density of air and v is the speed of sound.

From Equation (2) to (4), one can derive that the total loudness N can be expressed as a function of sound pressure RMS amplitude in the 24 Critical Band Rates (Bark):

$$N = f_N(P(1), P(2), \dots, P(z), \dots, P(24)) \quad (5)$$

The sharpness (in acum) which reflects the stridence degree of a sound is defined as:

$$S = k_2 \frac{\int_1^{24 \text{ Bark}} N'(z) \cdot z \cdot g(z) dz}{N} \quad (6)$$

Where k_2 is a constant coefficient, $g(z)$ is the weighting function defined by psychoacoustics.

Equation (6) shows that the sharpness is calculated by weighting on the loudness, which means that the sharpness can also be expressed as a function of sound pressure amplitude in Bark scale.

$$S = f_S(P(1), P(2), \dots, P(z), \dots, P(24)) \quad (7)$$

The connotation of Equation (5) and (7) is that the loudness and sharpness can be replaced by sound pressure RMS amplitude of each critical band as the input set of BPANN. In this case, noise signals are processed with 500Hz low-pass filter while the lower frequency of human hearing is 20Hz. According to ISO532B, five Critical Band Rates listed in Table 4 are in the frequency range in this case. Therefore, five sound pressure RMS amplitudes in the frequency ranges of corresponding Critical Band Rates are selected as inputs for the BPANN model.

Table 4. Five Critical Band Rates below 500Hz and its frequency ranges

Critical Band Rate (Bark)	Low frequency limit (Hz)	High frequency limit (Hz)
1	22	90
2	90	179
3	179	281
4	281	355
5	355	447

BPANN Modeling

The input layer of BPANN includes five neurons determined by the above discussion: sound pressure RMS amplitudes of noise samples in five different Critical Band Rates. For training the BPANN, an input vector is defined as:

$$IN = [P(1) \ P(2) \ P(3) \ P(4) \ P(5)]^T \quad (8)$$

The output layer with one neuron is the merit of subjectively evaluated Distraction Level. Node number of the hidden layer is determined referring to the empirical formula [23]:

$$m = \sqrt{n+k} + \alpha \quad (9)$$

Where, m , n and k denote the node number in the hidden layer, input layer and output layer respectively. For this case, $m=5$ and $n=1$. α is a constant, normally, $\alpha=1 \sim 10$.

From Equation (9) m may ranges from 4 to 13. To find an optimal m , a set of training test are performed by assuming m values from 4 to 13. The test results in Figure 4 suggest that, when $m=7$, the trained network reaches a minimum mean square error of 0.0383. Thus, the node number in the hidden layer is set to 7. Based on the above definitions, the BPANN is able to be trained to project the input of Bark scaled sound pressure amplitude vector to the output of predicted Distraction Level.

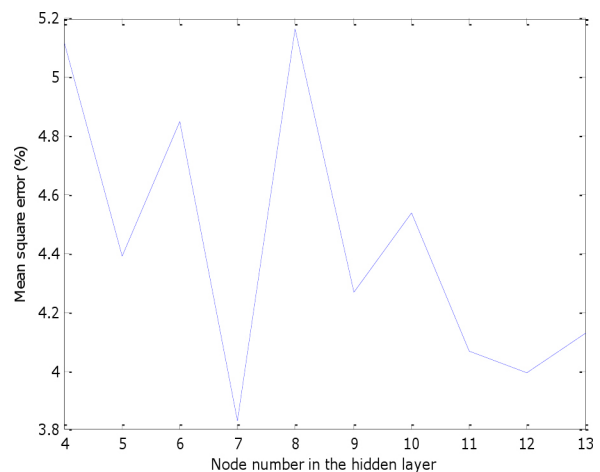


Figure 4. Mean square error of different node number in the hidden layer

The BPANN training procedure is performed by using Matlab program. Considering the non-linear characteristic of Distraction Level, the transfer function “tansig” and “purelin” are selected in the hidden layer and output layer respectively. The gradient descent with momentum weight/bias and the Levenberg-Marquardt algorithm are used in the network training. After a number of training epochs, the BPANN reaches convergence and stability. The correlation coefficient between targets and predictions showed in Figure 5 reaches a value of 0.959, which indicates that the BPANN model is capable of predicting the Distraction Level instead of using the subjective evaluation method.