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Design of new sound metric and its application for quantification of an axle gear whine sound by utilizing artificial neural network †

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Abstract

The gear whine sound of an axle system is one of the most important sound qualities in a sport utility vehicle (SUV). Previous work has shown that, because of masking effects, it is difficult to evaluate the gear whine sound objectively by using only the A-weighted sound pressure level. In this paper, a new objective evaluation method for this sound was developed by using new sound metrics, which are developed based on the increment of signal to noise ration and the psychoacoustic parameters in the paper, and the artificial neural network (ANN) used for the modeling of the correlation between objective and subjective evaluation. This model developed by using ANN was applied to the objective evaluation of the axle-gear whine sound for real SUVs and the output of the model was compared with subjective evaluation. The results indicate a good correlation of over 90 percent between the subjective and objective evaluations.

Keywords: Sound quality metric; SNR index; Axle whine noise; Neural network

1. Introduction

There are many different sound qualities inside of a car, such as those of the engine, road, wind, exhaust and other sounds, as shown in Fig. 1 [1-4]. These are the dominant sound sources that need to be reduced to a reasonable level since the sound pressure level due to them is considerably higher than that due to the other sounds and overrules the interior sound pressure level. Therefore, NVH (noise, vibration and harshness) engineers in the automotive industry try to reduce the sound pressure level due to these sound sources to as close to a marketable level as possible. However, if these sound pressure levels are reduced, the sound pressure levels due to the other component sources become dominant [5]. For example, the gear whine, which is generally masked by the major sources, becomes the important sound source. In particular, the axle-gear whine sound in a sport utility vehicle (SUV) becomes one of the dominant sound sources as the number of SUVs increases worldwide. It is sometimes difficult to evaluate the axle-gear whine sound objectively from the viewpoint of sound quality since it is embedded in the background sounds [6]. In this paper, considering this masking effect, a new metric is devel oped and used for the objective evaluation of the axlegear whine sound. This metric, called SNR (signal to noise ratio) index, is based on

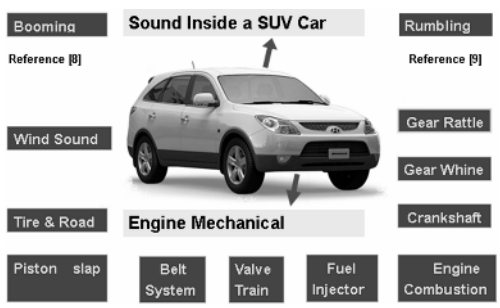

Fig. 1. Sound quality in the compartment of a passenger car.

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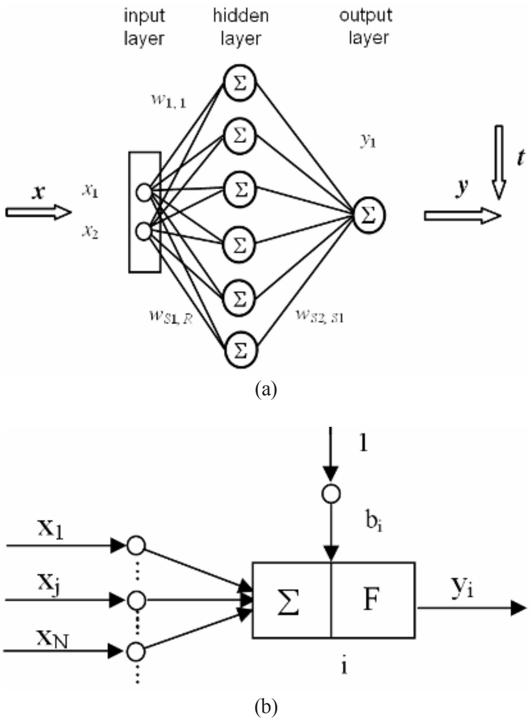


Fig. 2. Structure of artificial neural network for rumbling index: (a) three-layer, back-propagation network, (b) single neuron *i*.

the difference between the background sound and gear order sound. In addition, it was found that the loudness is also correlated with the axle-gear whine noise. These two sound metrics are used for the input of the ANN model, which is a tool to identify the correlation between the axle-gear whine index and the subjective evaluation for the axle-gear whine sound of an SUV. The multiple regressions have been used for modeling of sound quality of gear whine sound [7]. Recently, the ANN has been used for

sound quality analysis in automotive engineering [8, 9]. The structure of the ANN system used throughout this paper is shown in Fig. 2(a). The output of ANN, which is the objective rate of the axle-gear whine sound, is the axle-gear whine index developed throughout this study. If this objective rate has a good correlation with the subjective rating of the axle sound evaluated by passengers in SUVs, the output of ANN becomes a good axle-gear whine index. To use the output of ANN as the axle-gear whine index, one has to optimize the weights of connectors of the neurons in ANN throughout the training process. For the training process of ANN, 80 interior sounds with the axle-gear whine sound quality of various subjective ratings were synthesized by using the signal characteristics of the gear-gear whine sound, which are well known in many research papers [5-7]. Another five interior sounds of SUVs were obtained by measurement, and the axle-gear whine sound qualities for these interior sounds were subjectively evaluated by 21 persons for the target of ANN. This model developed by using ANN was applied to the objective evaluation of the axle-gear whine sound for real SUVS and the output of the model was compared with the subjective evaluations. The results indicate a good correlation of over 90 percent between the subjective and objective evaluations.

2. Artificial neural network theory

The ANN very loosely simulates a biological neural system (there is an extensive literature on ANN [10]); a multi-layer feed-forward network is used throughout this paper. The training algorithm used with this network is back-propagation [11], which is mostly used in the analysis of mechanics problems. The main goal of back-propagation neural networks is the map

ping of input, vector $x \in R^N$, into output, vector $y \in R^M$. This can be written in short as

$$x_{N\times 1} \rightarrow y_{M\times 1} , \tag{1a}$$

and in general

$$x^{(p)} \rightarrow y^{(p)} , \text{ for } \quad p = 1, 2,\ldots, p, \tag{1b}$$

where p is the number of patterns. The mapping is performed by a network composed of processing units (neurons) and connections between them. In Fig. 2(b) a single neuron i is shown. Input signals x_j are accumulated in the neuron summing block Σ and activated by function F to have only output y_i:

$$y_i = F(z_i), z_i = \sum_{j=1}^{N} w_{ij} x_j + b_i , \tag{2}$$

where z_i – active potential, $w_{i,j}$ –weights of connection, b_i – threshold parameter. Among various activation functions, sigmoid functions are commonly used:

$$F(z) = \frac{1}{1+e^{-\mu z}} \in (0,1) \quad \text{for } \mu > 0, \tag{3}$$

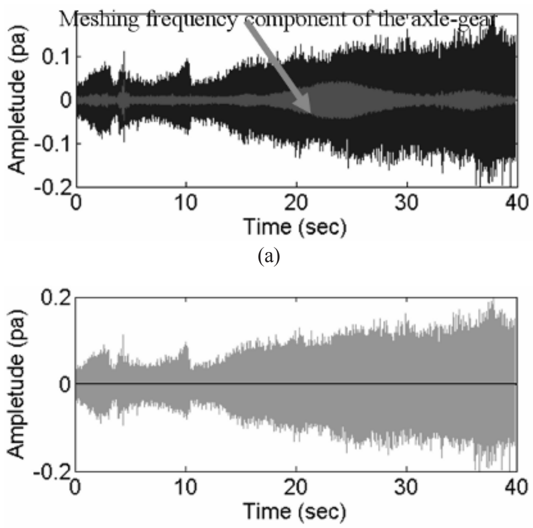
In Fig. 2(a), a standard multi-layer feed-forward network is shown. It is composed of the input, hidden and output layers, respectively. Each neuron is connected with all neurons of the previous and subsequent layers, but there are no connections inside the layer. An example of the network, shown in Fig. 2(a), is of 2-6-1 structure, i.e., there are $N = 2$ inputs; $H_1 = 6$ are numbers of neurons in hidden layers, and the output layer has $M = 1$ outputs. The weights $w_{i,j}^{l}$ and threshold b_i^l (where l is the number of the layer) are called the *network parameters*. The values of the network parameters are computed iteratively in the process of network training (learning). After training, the network should be tested. The input of ANN is also important. It should be correlated with the target of ANN to obtain optimized *network parameters*; otherwise, it is often difficult to obtain optimized *network parameters*

3. Synthetic axle-gear whine sound

To apply ANN to sound quality analysis, the optimal weights $w_{i,j}$ of connection of neurons in ANN, as shown in Fig. 2(b), should be obtained through a training procedure of ANN. For training of ANN, the various subjective rates for the axle-gear whine sound quality of the interior sounds of SUVs should be selected as the target of ANN. Thus, the mean-square-error for the difference between the subjective rate evaluated by a passenger and the objective rate, which is the output of ANN, should be minimized to obtain the optimal weights of the connections of neurons of ANN. As a result, a large number of interior sounds with the axle-gear sound quality of various subjective rates are required. It is difficult to obtain these kinds of interior sounds from mass-produced passenger cars, however, because most cars do not have a significant axle-gear sound problem due to development. Therefore, in this paper, those sounds are synthesized by using the information introduced in the many papers researched for enhancing the axle-gear whine sound quality. Basically, the interior sound of a car consists of very complex frequency spectrum since it has many excitation sources, resonance systems and parts of sound radiation [1-4]. However, it is known that the meshing frequency of the gear in the axle system influences the axle-gear whine sound quality [5-7]. Other frequency components play roles of background noise. Fig. 3 shows the time history for interior sound and meshing frequency component of the axle-gear. The horizontal axis designates time and the vertical axis shows the sound pressure level inside of the car. The car is accelerated with slow speed. The speed is divided by four different speed steps, and the exact center speed of each speed step is listed in Table 1. The signal is measured inside a reference SUV used for the production of 80 synthetic axle-gear sounds. Fig. 4(a) shows the image plot for STFT (short time Fourier transform) of the interior sound measured inside a reference SUV. The speed of the propeller shaft increases from 1000 rpm to 3500rpm. The acceleration duration is 40 seconds. In the figure, the horizontal axis designates the frequency and the vertical axis shows the rpm. From this figure, we can see that the sound pressure level at the meshing frequency of the axle-gear is dominant at high frequency and the meshing frequency is related to the rotating speed of the propeller shaft (i.e., rpm). At a low frequency, the dominant sounds are due to the engine sound and other background noise [1]. So if we change the am

Table 1. Speed step of peak position in the axle noise.

Speed step (Time shift)				
1	2	3	4	5
3.50s 48km/h	10.26s 65km/h	17.12s 81km/h	23.96s 98km/h	10.26 & 23.96s 65 & 98km/h



(b)

Fig. 3. Time history for the interior sound of a reference SUV car used for the production of the 80 synthetic axle-gear whine sounds: (a) meshing order (frequency) component for the axle-gear of an SUV, (b) 1, 2, 3 and 4 mean the different speed steps.

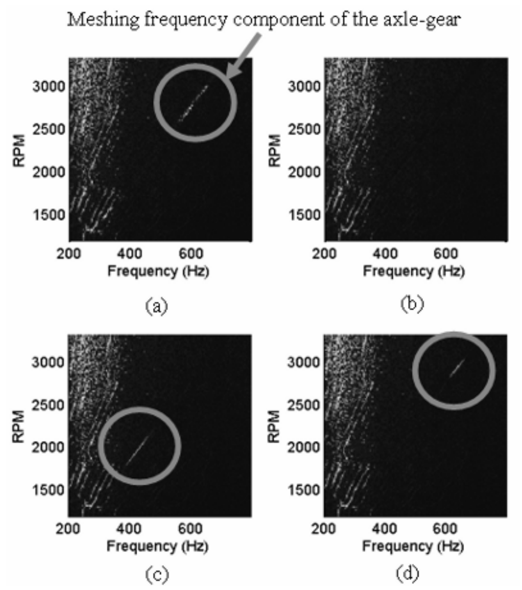


Fig. 4. Image plot for the interior sound of an SUV car: (a) original sound, (b) background oise without the sound component due to tooth meshing, (c) synthesized axle-gear sound located at low rpm, (d) synthesized axle-gear sound located at high rpm.

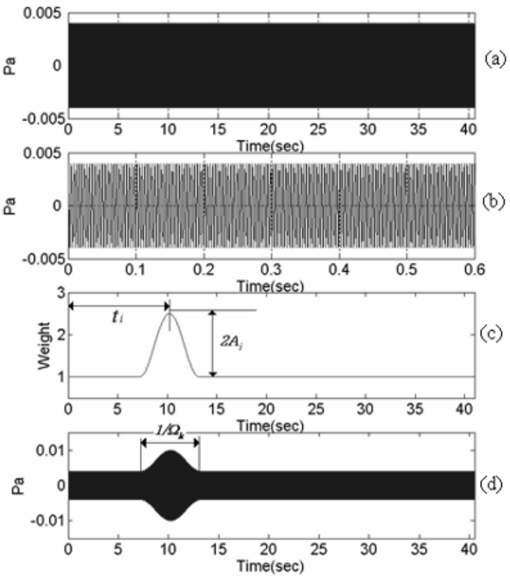


Fig. 5. Modification of meshing frequency component sound for production of the 80 interior sounds: (a) base meshing frequency component sound signal, (b) zoomed meshing frequency component sound signal, (c) design of the envelope weighting function, (d) modified base meshing frequency component sound signal with the axle-gear sound quality.

plitude of this meshing frequency component, the axle-gear sound quality for the interior sound of this car will also be affected. Mathematically, the time history of this component can be expressed as an analytic signal [12] with the amplitude and frequency modulated signal as follows:

$$x(t) = a(t)e^{j\phi(t)} \tag{4}$$

where $a(t)$ is the function associated with amplitude modulation (i.e., it is the envelope of the signal $x(t)$), and $\phi(t)$ is the function associated with frequency modulation. Fig. 5(a) represents the time history of the meshing frequency component sound. It is obtained by filtering the interior sound as shown in Fig. 4(a) with a Kalman order adaptive filter [13]. Fig. 4(b) shows the image plot for STFT of the interior sound obtained by removing the meshing frequency component of the original interior sound. The signal of the sound with only meshing frequency component is expressed as a form of the analytic signal explained in equation (4). The instantaneous frequency for the analytic signal [12] is given by

$$f_i(t) = \frac{1}{2\pi}\frac{d\phi(t)}{dt} \tag{5}$$

Therefore, if the speed of the propeller shaft is constant with meshing frequency f_0, the function $\phi(t)$ is given by

$$\phi(t) = 2\pi f_0 t \tag{6}$$

If the speed of the propeller shaft is changed with the meshing frequency $f_0 + f(t)$, then the function $\phi(t)$ is written by

$$\varphi(t) = 2\pi(f_0 + f(t)) \tag{7}$$

We can produce interior sounds with the axle-gear sound qualities of various subjective rates by modifying the envelope of the signal as shown in Fig. 5(a) and adding it to the background noise as shown in Fig. 4(b) because the background noise influences the axle-gear sound quality. In this paper, the envelope of the analytic signal is modified as follows (8):

$$\begin{cases} \mathscr{A}(t) = \left[A_j \sin\Omega_k(t - t_i) + A_j + 1\right] \cdot a(t), \\ \quad t_i - \dfrac{1}{2\Omega_k} \le t \le t_i + \dfrac{1}{2\Omega_k}, \quad i = 1,..5, j = 1..4, k = 1..4 \\ \mathscr{A}(t) = 1 \cdot a(t), \\ \quad \text{otherwise} \end{cases} \tag{8}$$

Table 2. Parameters used for production of the synthetic interior sound.

Time shift t_i (Center frequency)	Amplitude step A_j (Decibel ref.=2×10^{-5})	Duration $T_i=1/\Omega_k$ (Frequency Ω_k)
3.50s(200.35Hz)	0.75Pa(54dB)	6.05s(70Hz)
10.26s(373.75Hz)	1.2657Pa(57dB)	6.48s(75Hz)
17.12s(453.12Hz)	1.9941Pa(60dB)	6.91s(80Hz)
23.96s(532.38Hz)	3.0230Pa(63dB)	7.35s(85Hz)
10.26s and 23.96s (373.75Hz and 532.38Hz)		

where $a(t)$ is the envelope of the firing frequency component of the analytic signal; t_i is the i-th time where the amplitude modulation takes place; A_j is the j-th magnitude for presenting the magnitude of amplitude modulation; and Ω_k represents the k-th frequency for determining the duration of amplitude modulations.

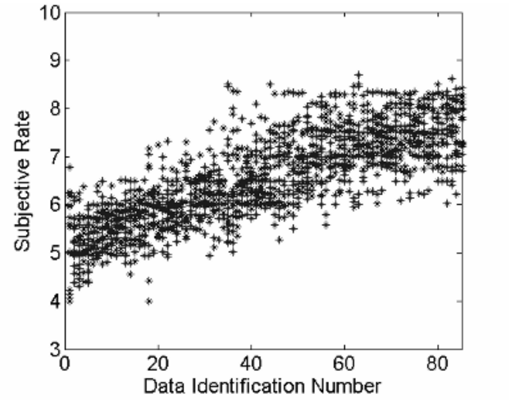
Table 2 presents the various values for the parameters Ω_k, t_i , and A_j used throughout this paper. Fig. 5(c) shows one example of the modified envelopes $\mathscr{A}(t)$ and illustrates the roles of the parameters. Fig. 5(d) displays the analytic signal $x(t)$ modified by using the modified envelopes $\mathscr{A}(t)$. The modified analytic signal is given by

$$x(t) = \mathscr{A}(t)\exp(j\phi(t)) \quad (9)$$

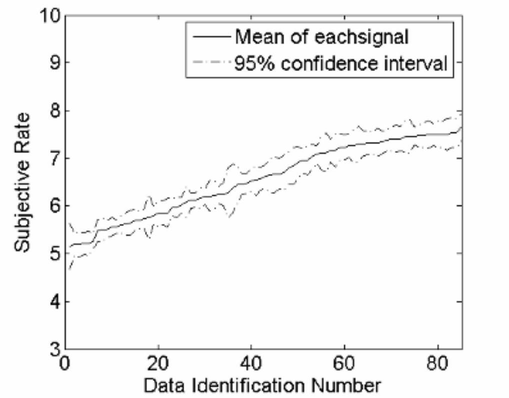
To get the synthetic interior sounds with different axle-gear whine sound quality, these modified analytic signals with various values for the Ω_k, t_i and A_j are added to the background noise as shown in Fig. 4(b). Fig. 4(c) and (d) shows the image plot for STFT of the interior sound for the synthetic interior sound by using a modified analytic signal as shown in Fig. 5. Fig. 4(c) shows the axle-gear whine sound located at low rpm, and Fig. 4(d) shows the axle-gear whine sound located at high rpm. With this method, the 80 synthetic interior sounds with the axle-gear sound quality of various subjective rates are completed. The subjective rates of these interior sounds are used for the target of the ANN.

4. Subjective evaluation

For the target of the ANN, the 80 synthetic interior sounds were subjectively evaluated by 21 NVH engineers (17 males and 4 females). In addition to the synthetic interior sounds, the interior sounds of five mass-produced SUVs were also used. The subjective evaluation therefore consists of a total of 85 interior sounds. A playback system and headphone of Head Acoustics Company were used for the subjective evaluation. The order of 85 interior sounds for subjective test was randomly chosen. The subjective rate was evaluated from point 4 to point 9. Table 3 illustrates the subjective rates and their relationship with the production guide of the SUVs. Fig. 6 (a) shows the results of the subjective evaluation for the 85 signals. The averaged subjective rates for 85 synthetic interior sounds are plotted from the left side of the graphic from low rate to high rate. Fig. 6 (b) illustrates the standard deviation with 95% confidence interval. It is calculated from all subjective evaluations of car individual interior sound. The subjective evaluation data within this deviation are used for the target of ANN.



(a)



(b)

Fig. 6. Subjective rates for the 85 interior sounds of passenger cars: (a) raw subjective rate, (b) averaged subjective rate and standard deviation with 95% confidence interval.

Table 3. Grade for subjective evaluation of the axle-gear sound quality.

Subjective rates	Production guide of cars
9	Very excellent
8.5	Excellent
8	Good
7.5	Acceptable for mass production
7	Marginal
6.5	Not good
6	Bad
5.5	Unacceptable to mass production
5	Very bad
4.5	Fail (Impossible to develop)

5. Sound metrics

The sound metrics for the 85 interior sounds were calculated for the input data of ANN. According to psychoacoustic theory [13], there are four major sound metrics: loudness, sharpness, roughness, and fluctuation strength. These metrics have been confirmed by psychoacoustic scientists. Many other sound metrics are developed for application to automotive engineering, such as SNR, tonality, kurtosis and sound pressure (dBA) depending on their application. In this paper, four major sound metrics – loudness, sharpness, and roughness and fluctuation strength and two more extended sound metrics, SNR index and tonality – were calculated. These sound metrics for 85 interior sounds are shown in Fig. 7(a) to Fig. 7(f). Among these metrics, the high correlated metrics with subjective rate are used for the input of the ANN to be used as the axle-gear whine index.

5.1 Loudness

Loudness represents the auditory perception character related to the magnitude of sounds [13]. Of the many models [13-15] for calculating the loudness, In this paper, the Zwicker model [13] is used to calculate the loudness for the 85 interior sounds. Loudness is measured in phones or sones; one sone is the loudness for a pure tone sound with amplitude of 40dB at 1kHz. Here, loudness is calculated for 85 interior sounds. In Fig. 7(a), loudness is plotted versus the subjective rating for 85 interior sounds. According to these results, the maximum loudness is about 3.2 sones. At this level, the average subjective rating is about 5.5. From the graphic, it is concluded that the subjective ratio is proportional to 1/loudness.

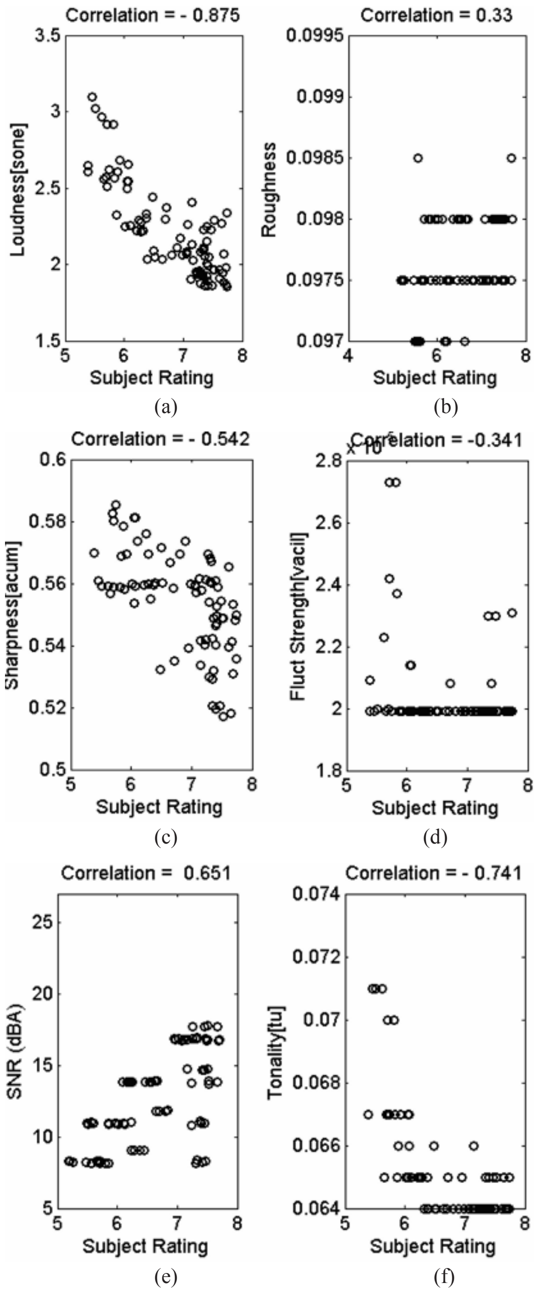


Fig. 7. Sound metric for the 85 interior sounds: (a) Loudness for the 85 interior sounds using Zwicker's method. (b) Roughness for the 85 interior sounds using Aures' model. (c) Sharpness for the 85 interior sounds using Bismarck's model. (d) Fluctuation strength for the 85 interior sounds using Fastl's model. (e) SNR index for the 85 interior sounds. (f) Tonality for the 85 interior sounds using Aures' model.

5.2 Roughness

Roughness is the auditory perception characteristic related to the amplitude modulation and frequency modulation for sound with frequency modulation at a middle frequency around 70Hz. It is related to the high frequency modulation of the sound. Aures [16] introduced a calculation model of roughness for sound; the unit of roughness is the asper. One asper is the roughness of a pure tone sound with an amplitude of 60dB at 1kHz that 100% modulated in amplitude at a modulation frequency of 70Hz. The roughness is calculated for 85 interior sounds. Roughness versus the subjective rating for these sounds is plotted as shown in Fig. 7(b), from which we can find that there is a very small relationship between roughness and human perception for the axle-gear whine sounds.

5.3 Sharpness

Sharpness describes auditory perception related to the spectrum correlation of a sound. Bismarck [17] and Aures [18] introduced a calculation model of sharpness. In this paper, Bismarck's model is also adopted. Sharpness is given by

$$S = 0.11 \times \frac{\int_0^{24} N' z g(z) dz}{N} \tag{10}$$

where N' is the specific loudness within the critical band (Bark) and g(z) is the critical band rate dependent weighting factor that is unity between 0 Bark and 16 Bark and then increases to four at 24 Bark. The unit of sharpness is the acum, which is the sharpness for a pure tone sound with amplitude of 60dB at 1kHz. The sharpness is calculated for 85 interior sounds. Sharpness versus the subjective rating for 85 interior sounds is plotted as shown in Fig. 7(c). According to these results, the maximum sharpness is about 0.59 acum, and it is difficult to conclude whether there is or is not a relationship between sharpness and human perception for the axle-gear whine sounds.

5.4 Fluctuation strength

Fluctuation strength is the auditory perception character related to the amplitude modulation and frequency modulation for sound with frequency modulation at lower frequency around 4Hz. Fastl and Zwicker [13] proposed a calculation model of fluctuation strength for sound. The unit of fluctuation strength is a vacil: one vacil is the fluctuation strength for pure tone sound with an amplitude of 60dB at 1 kHz that is 100% modulated in amplitude at a modulation frequency of 4Hz. The fluctuation strength is calculated for the 85 interior sounds. Fig. 7(d) is a plot of fluctuation strength versus the subjective rating for these sounds. From the graphic, the fluctuation strength has no relationship with human perception for axle-gear whine sounds.

5.5 Signal to noise ratio (SNR) index

Signal to noise ratio index is a quantitative measure of the signal with respect to background. Therefore, signal to noise rate is important for the identification of the pure tone sound is embedded background noise [7]. At constant speed of the propeller shaft, the meshing frequency component of the gear tooth generates the axle-gear whine sound inside a car. In general, this meshing frequency component is embedded in the background noise such as engine noise, tire noise, wind noise and other component noises inside a car. According to previous work, it is known that if the signal to noise ratio is over17dB, then axle-gear whine sounds are clearly identified. During acceleration, the meshing frequency component of the gear tooth is changed. Therefore, the minimum value of SNR_m for all synthetic sounds is calculated during acceleration of a car. The minimum value of SNR for each signal is selected as the sound metric. The correlation between subjective ratio and SNR_{min} is calculated and plotted as shown in Fig. 7(e). However, the correlation is not high level.

The reason for this low correlation is due to the change of the meshing frequency because the rotating speed of gearbox shaft increases during acceleration. The value of SNR for the identification of the axle-gear whine sound depends on the frequency or rpm. Therefore, in order to improve the correction a weight function is developed. The flow chart for the development of the weight function for this improvement is shown in Fig. 8. In the Fig.8, x_i is the original value of SNR_m at the i^{th} rotating speed of the propeller shaft in axle gearbox. x_{wi} is the value of weighted at the i^{th} rotating speed of the propeller shaft in axle gearbox, which is calculated by multiplying the original of SNR_m by the weight function w_i (i.e,. $x_{wi} = x_i \times w_i$). The value of correlation, R_{xy}, between subjective ratio y_j for j^{th} synthetic sound and minimum value x_{wi} of the weighted SNR_m is calculated. The calculation is repeated until the correlation becomes 0.9. Finally, the

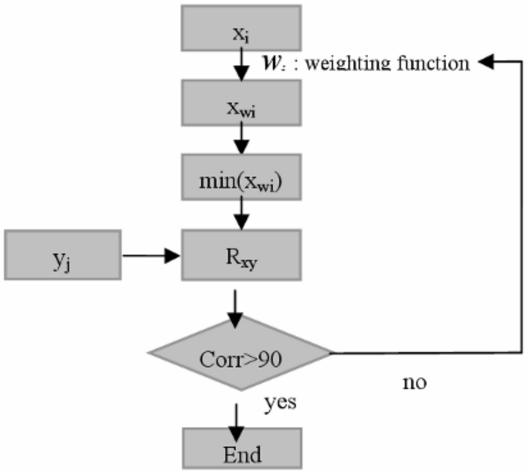


Fig. 8. The flow chart for the development of weight function for this improvement; (x_i : original minimum value of SNR_m., w_i: weighting function, x_{wi} : weighted minimum value SNR_{wm} ($x_{wi} = x_i \times w_i$), y_j : subjective rating for the j[th] sound, R_{xy}: calculation of correlation between the minimum value x_{wi} of SNR_m and subjective rating for the j[th] sound y_j).

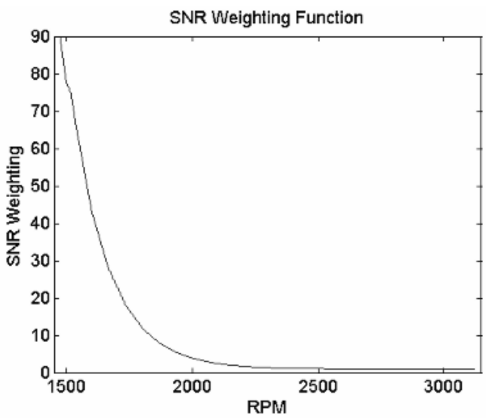


Fig. 9. Weight functions w_i for new SNR calculation.

weight function w_i is obtained and it is plotted as shown in Fig. 9. It's mathematically expressed by,

$$w_i = 0.0047 \times \exp(-0.45t + 10) + 1 \quad (11)$$

The minimum value x_{wi} of the weighted SNR is used as the new metric. The new calculated correlation between weighted minimum SNR_{wm} and subjective rating is calculated and is plotted as shown in Fig. 10. The correlation is improved from 0.657 to 0.918 as shown in Fig. 11. This new SNR is used for the sound metric as the input of ANN.

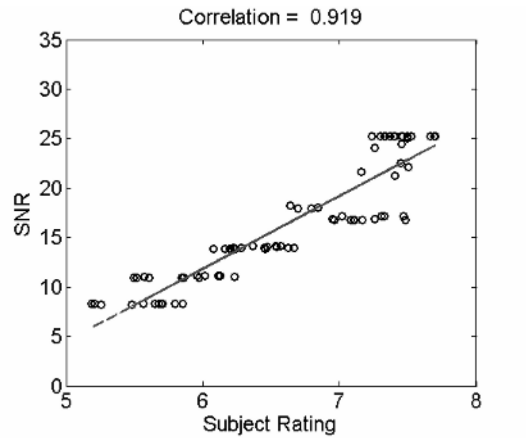


Fig. 10. Correlation between weighted minimum SNR_{wm} and subjective rating.

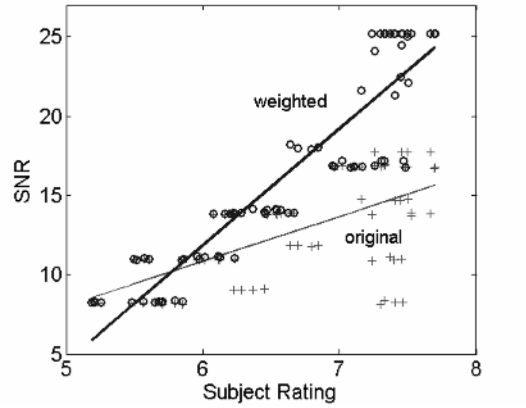


Fig. 11. Comparison between original correlation and improved correlation (x = the minimum value of original SNR, o = the minimum value of weighted SNR).

5.6 Tonality

Tonality represents the auditory perception character related to the pitch strength of sounds. There are many models for calculating the tonality. In this paper, the Aures model [19, 20] is used for the 85 interior sounds. Tonality is measured in tu; one tu is a 1kHz sine wave of 60 dB the sound pressure level loudness; this is the reference level. Tonality versus the subjective rating for 85 interior sounds is plotted as shown in Fig. 7 (f). From the graphic, the tonality has little relationship with human perception for the axle-gear whine, but there is no pattern for the relation with the subject evaluation.

The correlation between each sound metric and the

Table 4. Correlation between subject rate and sound metrics for the 85 interior sounds.

Loudness	Roughness	Sharpness
-0.875	0.33	-0.542
Fluctuation-Strength	SNR ratio	Tonality
-0.341	0.918	-0.741

subjective rating is listed in Table 4. From these results, loudness and SNR_m are chosen for the input of ANN since the correlation of these metrics exceeds 0.7. The other sound metrics have low correlation except for tonality as shown in Fig. 7(f). However, it cannot be used for sound metrics since the same tonality value has a different subject rating.

6. Axle-gear whine index using neural network

ANN has been applied to developing a booming index and rumbling index for sound quality analysis of automotive sound quality [8, 9]. In this paper, ANN is applied to the development of the axle-gear index of an SUV. Previous sections discussed the input and target for ANN; as shown in Fig. 2(a) the type of ANN used in the paper is the multiple-layer network. In this section the main work is to find the optimal weights $w_{i,j}$ of connections. The averaged subjective ratings and sound metrics for the 85 synthetic interior sounds were used for the optimization of the weights $w_{i,j}$ of connections of the ANN. Loudness and the SNR_m index of sixty synthetic sounds were used as the input for training of the ANN. Another twenty synthetic sounds were used for testing of the ANN. The ANN used as the axle-gear whine index consists of 2-6-1 structure, *i.e.,* $N = 2$, $H_1 = 6$ and $M = 1$. The number of weights of connects in the one hidden layer is six. Optimal weights are obtained by training of the ANN. Table 5 illustrates the optimal weights ($w_{i,j}$) of connects and threshold parameter (b_i) used at each layer. Mathematically, the axle-gear whine index using these optimal weights of connect and threshold is written by

$$\begin{aligned}&\text{axle-gear whine index}\\&= F^2(\mathbf{LW}^2F^1(\mathbf{IW}^1\mathbf{x}+\mathbf{b}^1)+\mathbf{b}^2)\end{aligned} \tag{12}$$

where the function F follows the form of Eq. (3), IW^1 is the weight matrix in the input layer, LW^2 is the weight matrix of the first hidden layer. The axle-gear whine index is the output of the trained

Table 5. Weight function and bias for the axle-gear whine sound index.

Weights of Input Layer $\mathbf{IW}^1$		Weights of hidden layer $\mathbf{LW}^2$
-0.035628	-0.87532	-0.35064
0.10921	1.0722	6.6125
-20.617	-2.0419	4.4875
3.2719	4.7569	-42.73
-11.912	-0.55135	0.82282
0.78438	2.9682	-54.317
Threshold of Input layer $\mathbf{b}^1$		Threshold of hidden Layer $\mathbf{b}^2$
-4.0318		-0.34007
0.95502		
-0.602		
-0.61653		
0.90827		
-1.1585		

ANN. Fig. 12 shows the correlation of the output of the ANN and the averaged subjective ratings of the sixty synthetic sounds used for the training of the ANN. In Fig. 12, the horizontal axis "T" means subjctive rating and the vertical axis "A" means the output of the ANN. They very much correspond and have a good correlation of 98.7%. Fig. 13 shows a comparison between the neural output and subjective rating for the training signals. These results are very well correlated. The axle-gear whine index by using the trained ANN is applied to the estimation of the subjective rating for another twenty synthetic interior sounds for a test of the trained ANN. These estimated subjective ratings are compared with the averaged subjective ratings of the twenty synthetic interior sounds. Fig. 14 shows their correlation, which is 99%. It can be used to estimate objectively the subjective ratings of the axle-gear whine sound qualities of an SUV without subjective evaluation by a skilled engineer. Finally, the trained ANN is applied to the estimation of the axle-gear whine sound quality of the five mass-produced SUVs. These results are plotted as shown in Fig. 15. The correlation between the averaged subjective ratings for five mass-produced SUVs and the output of the trained ANN is 96.9 %. Throughout these results, the axle-gear whine sound for an SUV is objectively evaluated by the trained ANN very well. Therefore, in order for an inexperienced engineer to evaluate the axle-gear whine sound using Eq. (11), the interior sound of an SUV should first be measured with a binaural head system and recorded. Second, the sound metrics of the recorded sound should be calculated by using methods explained in session 5. Finally, two sound metrics, loughness and SNR_m, are used for the input of Eq. (11). The weighting matrix and hreshold used in Eq. (11) are listed in Table. 5. This gear whine index is also applied to the production of a sound quality map as shown in Fig. 16. Fig. 16 shows the sound quality maps for the gear whine sound. The subjective rates for the gear whine sound of 5 passeneger cars are pointed out in the sound quality map in Fig. 16. This is a meaningful result for finding the relationship between sound metrics and sound qulaity level and the contribution of sound metrics to the sound quality pictorally.

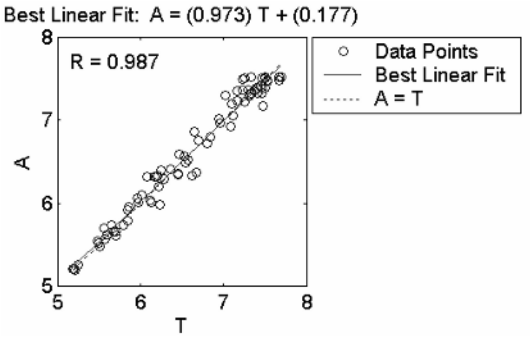


Fig. 12. Correlation between the output of the trained ANN and the averaged subjective ratings for the 60 synthetic interior sounds for the train of the ANN. The horizontal axis “T” means subjctive rating and the vertical axis “A” means the output of the ANN.

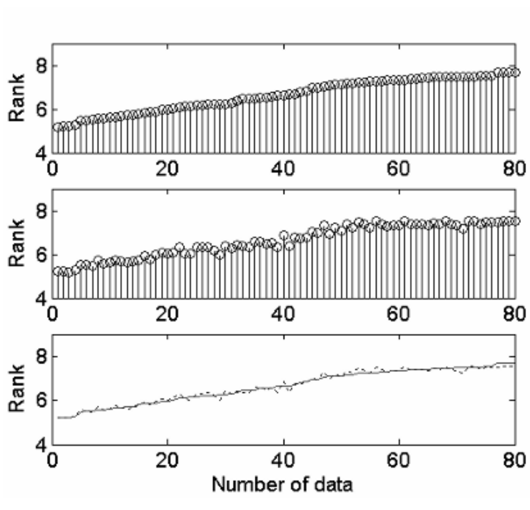


Fig. 13. Comparison between output of neural netwek and subjective rating (a) Subject rating. (b) Index output. (c) Comparison between subjective rating and index output.

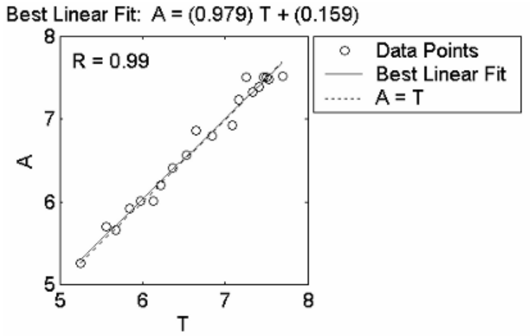


Fig. 14. Correlation between the output of the ANN and the averaged subjective ratings for the 20 synthetic interior sounds used for test of the ANN. The horizontal axis “T” means subjctive rating and the vertical axis “A” means the output of the ANN.

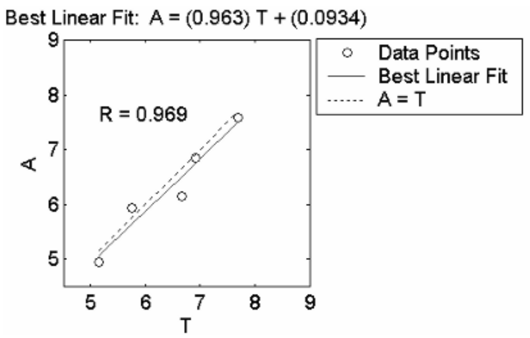


Fig. 15. Correlation between the output of the trained ANN and the averaged subjective ratings for the five interior sounds of the mass-produced SUV. The horizontal axis “T” means subjctive rating and the vertical axis “A” means the output of the ANN.

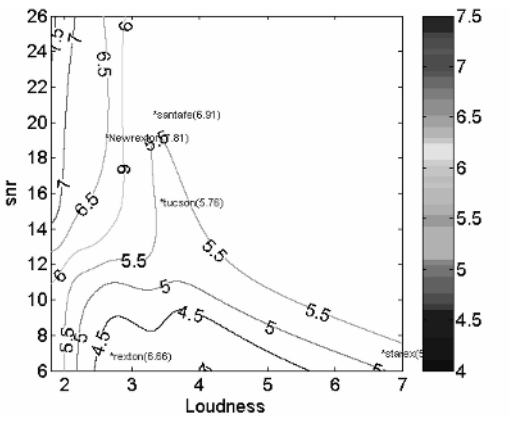


Fig. 16. Sound quality maps for axle gear whine noise.

7. Conclusions

The characteristics of axle-gear whine sound were investigated by using synthetic sound technology. Eighty axle-gear whine sounds were synthesized and evaluated subjectively by 21 NVH engineers. Throughout these tests, it was concluded that the axle-gear whine sound is affected by the speed of an SUV and the amplitude of the meshing frequency component of the interior sound. However, the time duration of the axle-gear whine sound does not affect the sound quality of the axle-gear whine sound. Throughout this characteristic, we can find intuitively that the loudness and high frequency dependent sound metrics are important.

An artificial neural network has been applied to the development of the sound quality index of the axle-gear whine sound of an SUV. The averaged subjective ratings for the interior sounds of 80 synthetic interior sounds were used for the development of the axle-gear whine index by using the ANN. For the training of the ANN, 60 synthetic sounds were used and 20 synthetic sounds were used for testing of the trained ANN. The ANN used in the present paper is a back-propagation neural network with 2-6-1 structure. The number of weights of connects in the hidden layer of the ANN is six. Loudness, sharpness, roughness, fluctuation strength, SNR and tonality for those interior sounds were calculated for the input of the ANN. It was found that loudness has a relationship with the averaged subjective ratings of those sounds. The correlation between the output of the trained ANN and the averaged subjective rating for those sounds is 96.3%. It is concluded that the output of the trained ANN can be used for the axle-gear index for the interior sounds of SUVs. This has been confirmed with the application of the trained ANN to the estimation of the subjective ratings for the axle-gear whine sound qualities of five mass-produced SUVs.

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