Stationary and Non-Stationary Vehicle Cabin Noise Level Identification Using Spectral Composite Features and Neural Networks

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Abstract

Determination of vehicle comfort is important because continuous exposure to the noise and vibration leads to health problems for the driver and passengers. In this paper, a vehicle comfort level classification system has been proposed to detect the comfort level in cars using artificial neural network. A database consisting of sound samples obtained from 30 local cars is used. In the stationary condition, the sound pressure level is measured at 1300 RPM, 2000 RPM and 3000 RPM. In the moving condition, the sound is recorded while the car is moving at 30 km/h up to 110 km/h. Subjective test is conducted to find the Jury's evaluation for the specific sound sample. The correlation between the subjective and the objective evaluation is also tested. The relationship between the subjective results and the sound metrics is modelled using Probabilistic Neural Network. It is found from the research that the Spectral Composite Feature gives better classification accuracy for both stationary and moving condition model, 94.21% and 90.45% respectively.

Keywords- noise comfort, subjective evaluation, noise level, frequency band, neural network.

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I. Introduction

Riding Comfort is the comfortness of noise, vibration and motion inside a vehicle, experienced by both driver as well as the passengers.

ISO 2631 whole-body vibration certification testing covers the comfort, safety and health of the passengers subjected to it [2]. The assessment of ride comfort consists of the four domains, namely, seat vibration, steering wheel vibration, interior noise and general handling in motion of the vehicle. Seat vibration deals with ISO whole-body vibration and absorption of vibration by the passenger and driver when on-board. Steering wheel vibration is due to tire unbalance. Interior noise in the vehicle deals with the averaged overall sound pressure level and sound metrics such as loudness, sharpness and roughness of the noise. General handling in motion of the vehicle is due to braking force, where it will affect the comfort of the passenger and driver in terms of drivability comfort. Measuring and quantifying ride comfort can help meeting the necessary standards and regulations. It also helps to troubleshoot, understand and improve the noise and vibration comfort in the vehicles [1].

The comfort in the car interior is already become a need for the passengers and the buyers. Due to high competition in car industries, all the car manufacturers are concentrating in improving the interior noise comfort of the car [7]. Although various researches and testing have been conducted, the researches are privatised for internal usage and are not commercialised. No specific device has been developed to test the comfort level in a vehicle commercially. Thus, there is a need to develop a user-friendly device which can be available to test the interior noise comfort commercially.

The rest of the paper has been organised as follows: Section 2 narrates the establishment of vehicle interior noise database. In Section 3, the feature extraction of the vehicle interior noise has been discussed. Section 4 shows the feature reduction using Principal Component Analysis. Section 5 discusses the formulation of Spectral Composite Feature. The subjective evaluation on the noises is described in Section 6. Section 7 discusses about the experimental prediction and verification. The paper is concluded in Section 8.

II. Establishment Of Vehicle Interior Noise Database

The methodology for the research is divided into two sections, namely objective evaluation and subjective evaluation.

Data is required to train and test the artificial neural network for maximum classification accuracy. Thus, a simple data recording protocol is formulated to record the noise level inside the car. A measurement mannequin is used to place the microphones and the wirings as per ISO 5128-1980 (E) Acoustic- Measurement of noise inside motor vehicles standard [6, 15]. The sampling frequency of the recorded sound is 51200 Hz. It is further re-sampled to 8000 Hz [10]. Human ears are sensitive from 8 Hz to 4000 Hz and the sensitivity will decrease gradually when the frequency approaches 20 kHz. 8000 Hz is chosen based on two times the maximum frequency required as defined by Nyquist sampling theorem.

During the measurement sessions, the measurement mannequin is placed on the front passenger seat. Figure 1 shows the position of the mannequin in the car. Two microphones need to be placed at front portion and another at the rear portion of the car interior [15]. The front microphones are attached to the headphone which is placed on the mannequin's head. Figure 2 shows the position of microphones on the mannequin's head. The measurement device is placed on rear seat of the car as shown in Figure 3. All the microphones are connected to the measurement device, Orchestra. The Orchestra's input channels are used to capture the input signals. One crew is required to operate the car while another to control the data recording [15].

Figure 1. Experimental Set-up using Measurement Mannequin

For data collection, two measurement sessions are conducted. The first measurement session is conducted when the car is in stationary condition (SC). The engine has been accelerated to three different speeds, namely, 1300 RPM, 2000 RPM and 3000 RPM [15]. The relationship between the speed of the car and the Revolution per Minute (RPM) has been utilised. For each trial, the noise inside the car is recorded for 10 seconds. For the measurement during moving condition (MC), the car is driven at a constant speed at 30 km/h, 60 km/h, 70 km/h, 80 km/h, 90 km/h and 110 km/h respectively and the noise inside the car is measured [18].

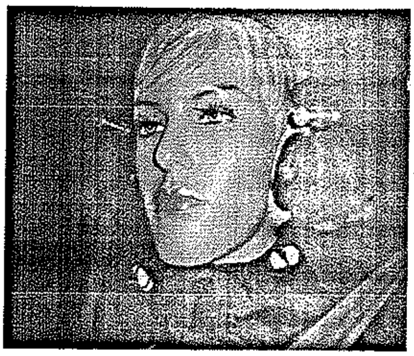

Figure 2. Microphone Positions on Measurement Mannequin

The recorded sound samples contain additional environmental noise. The data collection has to be done in a sound-proof room to get the data with minimum noise, but it is not feasible to implement in the outdoor condition, especially for data collection when the car is moving. Hence, a simple pre-processing is performed on the recorded signals. The low frequency component below 8 Hz and high frequency noise components above 4000 Hz are removed using band-pass Butterworth Filter with order 1 [9, 11]. 25 One-third Octave frequency bands with 25 centre frequencies are used for signal filtration.

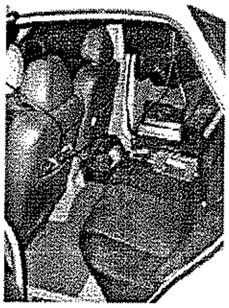

Figure 3. Experimental Set-up using Measurement Mannequin

III. Feature Extractions of Car Interior Noises

Feature extraction involves simplifying the amount of resources required to describe a large data accurately. For sound signal, basic statistical features such as the mean, median, standard deviation, energy and kurtosis can be taken. Many popular researchers those involved in acoustic researches prefer sound quality metrics such as the loudness, sharpness, fluctuation strength and roughness to be used as the features [8, 16]. In this paper, One-third frequency band power, L_{eq}, energy entropy and loudness are used as features [17].

Each signal is divided into frames such that each frame has 1024 samples [13, 18]. 1024 samples were chosen since it gives a better result when compared to other 2^n values; where n is a value from 1 onwards. The frame signals are filtered using 25 one-third octave band Butterworth filters with band range between 8Hz to 4000Hz. The high frequency noise is filtered since the significant comfort variation happens mainly between 8Hz to 4000Hz [18]. The features values are normalised between values 0.1 to 0.9 using binary normalization technique and have been randomised [3].

Four features were discussed and compared. The four features are discussed below:

A. Spectral Power (SP)

In SP feature extraction process, the signal was first Fourier transformed. Using Equation (1), the SP values for the twenty five bands corresponding to a frame are computed.

$$p_i^k = \sum_{q=1}^{N}[Y_i^k(q)]^2 \qquad (1)$$

where,

$N = 1024$, is the number of samples,

$Y_i^k(q)$ represents the q^{th} sample of the k^{th} frame corresponding to the i^{th} frequency band, and

p_i^k represent the i^{th} frequency band of the k^{th} frame signal.

$$P^k = [p_1^k\ p_2^k\ p_3^k \ldots p_{25}^k] \qquad (2)$$

The SP corresponding to the k^{th} frame is represented in Equation (2). A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Power (SC-SP) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Power (MC-SP) database.

B. Spectral Equivalent Continuous Sound Pressure Level (SLEQ)

The signal was first Fourier transformed. The SLEQ values for the twenty five bands corresponding to a frame are computed using Equation (3).

$$l_{eq_i}^{\ k} = \sum_{q=1}^{N}\left[10\ \log_{10}\left(\frac{1}{T}\int_{Q}^{T}\left(\frac{P(t)}{P_0}\right)^2\left(Y_i^k(q)\right)dt\right)\right] \quad (3)$$

where, $N = 1024$, is the number of samples,

$Y_i^k(q)$ represents the q^{th} sample of the k^{th} frame corresponding to the i^{th} frequency band, and

$l_{eq_i}^{\ k}$ represents the i^{th} frequency band of the k^{th} frame signal.

$$L_{eq}^{\ k} = [l_{eq_1}^{\ k}\ l_{eq_2}^{\ k}\ l_{eq_3}^{\ k} \dots l_{eq_{25}}^{\ k}] \quad (4)$$

The SLEQ corresponding to the k^{th} frame is represented in Equation (4). A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Equivalent Continuous Sound Pressure Level (SC-SLEQ) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Equivalent Continuous Sound Pressure Level (MC-SLEQ) database.

C. Spectral Energy Entropy (SEE)

In SEE feature extraction process, the signal was first Fourier transformed. Using Equation (5), the SEE values for the twenty five bands corresponding to a frame are computed.

$$s_i^k = -\sum_{q=1}^{N}[(Y_i^k(q))^2\ \ln(Y_i^k(q))^2] \quad (5)$$

where, $N = 1024$, is the number of samples, represents the q^{th} sample of the k^{th} frame corresponding to the i^{th} frequency band, and represent the i^{th} frequency band of the k^{th} frame signal.

$$S^k = [s_1^k\ s_2^k\ S_3^k \dots s_{25}^k] \quad (6)$$

The SEE corresponding to the k^{th} frame is represented in Equation (6). A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Energy Entropy (SC-SEE) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Energy Entropy (MC-SEE) database.

D. Spectral Loudness (SL)

The signal was first Fourier transformed. The SL values for the twenty five bands corresponding to a frame are computed using Equation (7).

$$l_i^k = -\sum_{q=1}^{N}\left[\int_0^{24\ Bark} L\left(Y_i^k(q)\right)dz\right] \quad (7)$$

where, $N = 1024$, is the number of samples,

$Y_i^k(q)$ represents the q^{th} sample of the k^{th} frame corresponding to the i^{th} frequency band, and

l_i^k represent the i^{th} frequency band of the k^{th} frame signal.

$$L^k = [l_1^k\ l_2^k\ l_3^k \dots l_{25}^k] \quad (8)$$

The SL corresponding to the k^{th} frame is represented in Equation (8). A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Loudness (SC-SL) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Loudness (MC-SL) database.

IV. Feature Reduction Using Principal Component Analysis

The most well known linear method for data analysis is the Karhunen-Loeve transform or the Principal Component Analysis (PCA) method, which maximises the variance of the projected vectors. It is defined by a matrix having as rows the eigenvectors of the feature space covariance martix. The PCA removes any redundancy between the components of the projected vectors, since the covariance matrix in the transformed space becomes diagonal as shown in (9):

$$\Sigma y = diag[\lambda_1\ \lambda_2\ \lambda_3\ \dots\ \lambda_n] \qquad (9)$$

where,

λ_i, $i = 1,2,3,\dots,n$ stand for the eigenvalues of the decomposed data covariance matrix.

The PCA performs the vector projection without any knowledge of their labels. This transformation is defined in such a way that the first principal component has as high a variance as possible and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. It is therefore, an unsupervised data analysis method.

In this research, PCA was used to remove any redundancy between the components of the projected vectors in each frequency bands. Only relevant data were chosen, ignoring components whose variance explained is less than 1. Table 1 shows the number of reduced data column using PCA. The most number of data column were reduced for SLEQ, showing that the feature has the most redundancy of data.

Table 1. Comparison of Number of Data Columns Before and After PCA

Features	Before PCA	After PCA
SP	25	22
SLEQ	25	19
SEE	25	21
SL	25	20

V. Formulation of Spectral Somposite Feature

Using PCA, the best set of values of each features were obtained. The obtained features can be combined to form a more robust and better feature. This is called Composite Feature (CF). In this research, a set of CF was formed, namely, Spectral Composite Feature (SCF). SCF is formed by combining all the reduced data columns of the time domain features.

Procedure to extract the frame based SCF features is described below:

Step 1 : The reduced data columns after the PCA (Table 1) of each spectral feature for SC protocol were combined. The SCF set for the k^{th} frame corresponding to the i^{th} data column obtained from the four spectral features can be represented as:

$$SCF^k = [p_1^k\ p_2^k\ p_3^k \dots p_{22}^k\ {l_{eq_1}}^k\ {l_{eq_2}}^k\ {l_{eq_3}}^k \dots {l_{eq_{19}}}^k$$
$$s_1^k\ s_2^k\ s_3^k \dots s_{21}^k\ l_1^k\ l_2^k\ l_3^k \dots l_{20}^k]$$

Step 2 : A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Composite Feature (SC-SCF) database.

Step 3 : Repeat step 1 for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Composite Feature (MC-SCF) database.

VI. Subjective Evaluation On Car Interior Noises

The recorded signal is converted from *.cmg* into *.wav* files to be played back to the juries [14]. The *.cmg* format raw data file is obtained using the dBFA32 post-processing software. 20 Jury members are chosen from the School of Mechatronics Engineering, University of Malaysia Perlis (UniMAP).

Hearing screening is conducted using pure tone audiometric test. The test is vital to identify whether the subject is having normal hearing capability or not. The subjects can only proceed to the listening test if they passed the pure tone audiometric test [4, 19]. The test is conducted in the Acoustic lab using the Audiometric chamber. Prior to the test, the audiometric booth was calibrated by the certified vendor, so that the results from the test are acceptable. The baseline audiogram for each subject is stored for future references [14].

The subjects are allowed to sit for the listening test only if they pass the hearing screening test. The listening test is conducted in a small closed room to generate the environment of car interior. The recorded sample is stored in compact disks in randomized manner and played to the subjects [10]. The subjects need to listen to the samples played using the laptop and give the evaluation for the specific recorded sample. The subjects need to give the evaluation for the noise comfort based on the scale 1 to 10, where the scale 1 indicates least comfort and 10 indicates the most comfort level [12].

Table 2. Subjective Evaluation Output Distribution

Subjective Rating	Stationary Condition	Moving Condition	Total Rating
1	23	21	44
2	26	25	51
3	36	36	72
4	64	92	156
5	102	166	268
6	93	135	228
7	45	78	123
8	34	82	75
9	33	44	77
10	24	41	106
Total:	480	720	1200

The recorded sample is played at the actual sound pressure level recorded in the car, so that the subjects can have the same sound exposure experienced during the measurement sessions. The sound samples are played back using headphones, so that the subjects get the same sound exposure and are protected from unwanted disturbing noise [5, 10]. The maximum allowed sound pressure level to be played is 90dB. Continuous exposure to noise above 90 dB can leads to temporary deafness and permanent deafness.

After obtaining the subjective indices from all the subjects, the average index is computed and used as the target value for training the neural network. It is important that the outlier removal is made on the subjective ratings to ensure that the subjective rating is reliable. The standard deviations of the sound samples are shown in Table 2. From Table 2, it can be inferred that most of the subjects rate the sound samples from 4 to 7. The extreme ratings are the least rated by the subjects.

VII. Experimental prediction and verification

Artificial neural network is a powerful tool used in many applications such as pattern recognition, data processing and classification. Artificial Neural Network imitates the biological neural network of human brain. It produces the output pattern when given the input pattern. It is an information processing system developed as a generalisation of mathematical models of human cognition [20]. In this research, Probabilistic Neural Network (PNN) is used to classify the cars comfort at different conditions [20]. PNN is chosen since it gives better classification accuracy and has less computational time when compared to the conventional Multilayer Perceptron classifier. For every feature, two neural network models are developed, one for stationary condition and another one for moving condition. Both the network model consists of 28 input neurons in the input layer and two hidden layers with 40 hidden neurons each. The 28 input neurons are the values from 25 frequency bands and the remaining 3 inputs indicate the speed information (each recorded speed was represented using a 3-bit binary code). The SCF model has total number of 85 input neurons, 82 input neurons obtained from the four features after PCA and 3 input neurons to indicate the speed information. All the network model has ten output neurons. The binary sigmoid activation function is used since the data samples are normalised from 0.1 to 0.9. The SC-SCF contains 720 samples and the MC-SCF database contains 480 samples. The ratio for training and testing data is modelled as 60/40 [20].

Table 3 shows the neural network training result for the stationary condition for all the four features and the composite feature. From the table, it is observed that SCF offers better mean classification rate of 94.21%. SLEQ recorded the least mean classification rate of 89.53%.

Table 4 shows the neural network training result for the moving condition for all four features and the composite feature. From the table, it is observed that SCF offers better mean classification rate of 90.45%. SL value records the least mean classification rate of 85.43%.

Table 3. Classification Accuracy Of Stationary Condition

	SP	SLEQ	SEE	SL	SCF
Minimum Classification Rate (%)	90.12	88.00	88.33	87.33	91.12
Maximum Classification Rate (%)	92.31	90.81	90.67	90.86	95.88
Mean Classification Rate (%)	91.42	89.53	89.62	89.57	94.21

Based on the comparison in Figure 4, SCF gives the best result for both the condition. Both moving and stationary models are used to evaluate the noise comfort level in the vehicle.

Table 5 and Table 6 show the confusion matrix of SCF feature for both stationary and moving models respectively. From Table 5, it is observed that the first, second, ninth and tenth indices have no level of confusion and it is classified accurately. Further, it is observed that the seventh index has high level of confusion when compared to the other indices. From Table 6, it is observed that the first index has low level of confusion and it is classified accurately. Further, it is observed that the fourth index has high level of confusion when compared to the other indices.

Table 4. Classification Accuracy of Moving Condition

	SP	SLEQ	SEE	SL	SCF
Minimum Classification Rate (%)	86.18	84.51	85.32	84.33	88.56
Maximum Classification Rate (%)	88.83	87.57	87.75	87.75	91.75
Mean Classification Rate (%)	87.40	86.37	86.59	85.43	90.45

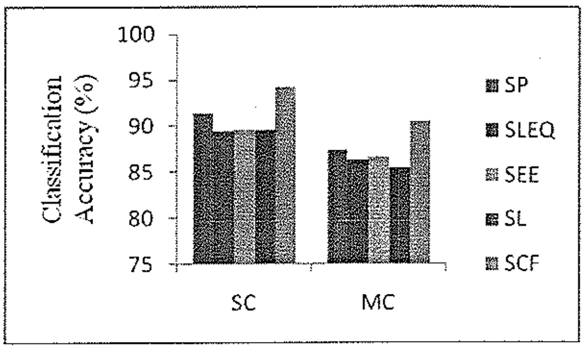

Figure 4. Comparison between the features

TABLE 5. CONFUSION MATRIX OF SC-SCF

Actual	Predicted										
	Index	1	2	3	4	5	6	7	8	9	10	Accuracy (%)
	1	6	0	0	0	0	0	0	0	0	0	100.00
	2	0	8	0	0	0	0	0	0	0	0	100.00
	3	0	0	9	0	0	0	0	1	0	0	90.00
	4	0	1	0	23	0	0	1	0	0	0	92.00
	5	0	2	0	0	52	0	0	0	0	0	96.30
	6	0	0	0	0	1	31	0	0	1	0	93.94
	7	0	1	0	1	0	0	21	0	1	0	87.50
	8	0	0	0	0	1	0	0	16	1	0	88.89
	9	0	0	0	0	0	0	0	0	11	0	100.00
	10	0	0	0	0	0	0	0	0	0	3	100.00

TABLE 6. CONFUSION MATRIX OF MC-SCF

	Predicted											
	Index	1	2	3	4	5	6	7	8	9	10	Accuracy (%)
Actual	1	6	0	0	0	0	0	0	0	0	0	100.00
	2	0	9	0	0	2	1	0	1	0	0	90.00
	3	0	1	12	0	0	0	1	0	0	0	85.71
	4	0	2	0	27	2	0	1	0	0	0	84.38
	5	0	1	2	0	82	0	1	0	2	1	92.13
	6	0	1	2	0	0	58	1	1	0	0	92.06
	7	0	0	0	0	0	1	21	0	0	1	91.30
	8	0	0	0	2	0	0	0	22	1	0	88.00
	9	0	0	0	0	0	1	0	0	13	0	92.86
	10	0	1	0	0	0	0	0	0	0	8	88.89

VIII. Summary and Conclusions

The research covers the concepts of digital signal processing techniques and artificial neural network. Measurement device, Orchestra is used to capture the noise emanated from the vehicle interior. The frequency-based features, namely, Spectral Power, Spectral L_{eq} value, Spectral Energy Entropy, and Spectral Loudness were extracted from the signals. The sound is played back to 20 subjects with good hearing capabilities to find out the associative index for the respective sound file. Based on the neural network training, it has been observed that Spectral Composite Feature gives the best result for both moving and stationary models. Confusion matrices of Spectral Composite Feature for both models have been tabulated.

Acknowledgement

The authors would like to acknowledge the support and encouragement given by the Vice Chancellor of University of Malaysia Perlis (UniMAP), Brig. Jeneral Dato' Prof. Dr. Kamaruddin Hussin. The research is conducted in University of Malaysia Perlis. This work is financially assisted by the Fundamental Research Grant Scheme (FRGS): 9003-00186 by Ministry of Higher Education, Malaysia.

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