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Development of Sound Quality Index for Quantification of Sporty Vehicle Engine Sound and Methods for Index Accuracy Improvement

차량의 스포티한 엔진음 정량화를 위한 음질 지수 개발과 그 정확도 향상을 위한 방법 연구

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Development of Sound Quality Index for Quantification of Sporty Vehicle Engine Sound and Methods for Index Accuracy Improvement

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ABSTRACT

Development of Sound Quality Index for Quantification of Sporty Vehicle Engine Sound and Methods for Index Accuracy Improvement

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Developments in vehicle technology and accompanying improvements in NVH performance have led to increased consumer demand for high sound quality, such as a “sporty” engine sound. As sporty sound is subjective, this thesis sought to express its meaning quantitatively and to develop a model that accommodates the differences in individuals’ tastes. This thesis tackles two main issues. The first is to identify the efficiency of factor analysis for utilizing it in developing a sound quality index of sportiness. The second is to further

improve the accuracy of the sound quality index and to refine the definition of sportiness by adding K-means cluster analysis.

In Chapter 2 and 3, the initial procedure for developing the sportiness index is presented. Accordingly, the process of recording the vehicle’s interior operating sound under wide open throttle acceleration conditions for 4 different vehicles and producing 13 evaluation samples by using parametric band-pass filtering is described. Acoustic and psychoacoustic parameters of the samples produced were calculated, and the preferences for sportiness were identified through jury testing. Jury test was jointly carried out by 23 evaluators and a semantic differential method was used to find adjectives that could explain the concept and preference for sportiness. The “Sportiness” index was developed using factor analysis and multiple linear regression analysis between the calculated values and the previously collected jury test results. The index was then validated by examining the correlation coefficient through a new sample group. Furthermore, the necessity of factor analysis for the sportiness index development was concluded. In Chapter 4, after K-means clustering, factor and multiple linear regression analysis were repeated to develop a model reflecting differences for each group in evaluator’s tastes. The improved index

was also retested using new evaluators and new samples, demonstrating its reliability through the high correlation observed in the validation studies.

This sound quality evaluation index is useful for producing highly accurate results and reflecting the opinions of groups expressing a variety of commonalities.

Keywords: Sound quality index, Vehicle engine sound, Sportiness, Semantic differential method, K-means clustering, Factor analysis, Multiple linear regression

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CHAPTER 1

INTRODUCTION

This study sought to determine how to identify a "sporty engine sound" in terms of sounds from an engine, which is the main source of sound generated by a vehicle. Moreover, the study sought to determine how to objectify the subjective concept of "sportiness" and increase its accuracy. To achieve these objectives, we focused on classifying the tastes of evaluators by analyzing preferences with regard to the engine sounds people would feel are "sporty" and by applying the K-means clustering algorithm. The study additionally applied a multiple linear regression analysis based on the classified values to derive regression equations, thereby quantifying the results.

Recently, the influence of AI, arising from the Fourth Industrial Revolution [1], has also been felt in the field of noise, vibration, and harshness (NVH). Electric vehicles and the like may also reduce interest in internal combustion engines, which are still the main power sources for most vehicles. However, because of various factors including marketability, supply infrastructure, and price issues, there is still a need for competitive and ongoing research [2]. Furthermore, in the last few decades, there has been a rise in consumer demand for good sound rather than for simple noise reduction in internal combustion engines. Consequently, researchers must continuously investigate the quality of various sounds generated by vehicles in addition to those of the engine. Many relevant results are presented here. Kwon et al. identified the sound quality metrics that have an effect when loudness is excluded, which normally dominates vehicle interior sound to provide a sporty image [3]. He et al. proposed a structure–loudness model to represent exhaust tail noise according to structural differences in the exhaust system [4]. S. K. Lee et al. proposed a method to predict changes in the sound inside a car cabin with respect to variations in absorption materials [5]. In addition, researchers have investigated methods for improving and objectifying various types of vehicle-generated noise, including window movement sounds [6-7], car horn sounds [8], and the buzz, squeak, and rattle from the instrument panel [9].

However, although many sound quality indices are being developed, providing accurate answers for the target sound or concept is a difficult problem because it is influenced not only by individual preferences but also by regional and cultural differences [10]. Thus, research that aims to produce highly accurate equations can yield very useful results. One of the approaches to gradually increase the accuracy of the indices involves applying various methods including regression analysis on a trial and error basis. These attempts will eventually help us develop the ideal indices we require. Lee used an artificial neural network (ANN) to create sound quality indices for booming and rumbling sounds that occur during driving [11], and Cerda et al. proposed a method for classifying and grading the characteristics of halls by extracting common variables into representative factors by using factor analysis [12]. This study had two main objectives. The first was to determine which engine sounds people feel are sporty and objectively define them through sound quality evaluation and to identify the effects as well as the necessity and effectiveness of factor analysis. The second was to derive more detailed results by clustering the data. The second objective is a follow-up to an earlier study [13-14]. Based on our finding that evaluators' concepts of sporty sound are divided, we classified similar characteristics through clustering and created indices to reflect the opinions of minority groups.

Nopiah et al. proposed a k-NN algorithm with more accurate results than those of previous neural networks and then used it to develop a model that can evaluate vibration levels in a vehicle cabin without subjective testing [15]. Pietila and Lim conducted a study to efficiently identify and classify juries for small-engine sound using K-means clustering and Ward's clustering method [16]. Yunoh et al. used an artificial neural network and K-means clustering for fatigue strain signals to find the optimal levels of fatigue damage [17]. In addition, studies have been carried out utilizing cluster analysis to classify marketing problems, climate data, casino gambling motivations, and the characteristics of offshore workers [18-21]. Cluster analysis is a tool used across various fields such as computer science, social science, medicine, psychology, and business administration. However, it is used relatively less in the automobile field. In addition, as there are still limitations in developing indices of sporty sound that can accommodate all opinions, research is needed to obtain accurate equations through segmentation using clustering.

Accordingly, the study was conducted according to the flow chart given in Fig. 1.1, and this thesis is structured as follows: Chapter 2 covers the general procedures relating to sound quality, including vehicle experiments, sample production, and jury testing. Chapter 3 and Chapter 4 describe the statistical process for examining the correlation between the objective data and the subjective test results based on factor analysis and K-means cluster analysis, respectively. Chapter 5 concludes the thesis by summarizing the findings and discussing the results.

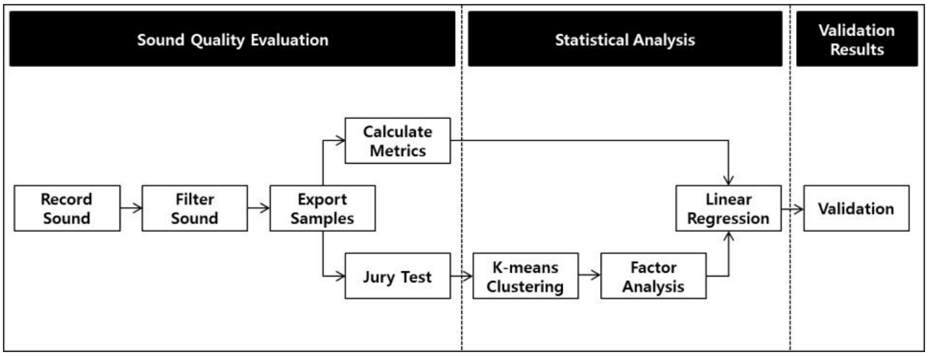


Figure 1.1 Flow chart of the research process.

CHAPTER 2

SOUND QUALITY EVALUATION OF VEHICLE ENGINE SPORTINESS

2.1 Introduction

This chapter describes the sound quality evaluation process for deriving an evaluation model for the target sound or image. It covers the entire process until sound quality evaluation (Fig. 1.1), which includes recording the engine sound to producing sounds using a filter, calculation of the acoustic and psychoacoustic parameters (which are the objective values of the sounds), and the jury test process to determine how people think about sportiness on hearing the sounds.

2.2 Sound recording and objective evaluation of engine sound

2.2.1 Recording of interior sound

To identify and materialize a concept for what people think of as "sportiness," an engine sound that can be played for people to hear is needed. Thus, in preparation for producing such samples, we recorded the driving sound of actual vehicles. Four vehicles (three benchmarking vehicles and one target vehicle) were selected from among vehicles in the market that consumers perceive as sporty. Two were 4-cylinder engines, and two were 6-cylinder engines; all were gasoline engines. Fig. 2.1 shows the data acquisition process for objective evaluation and Table 2.1 shows the specifications of the test vehicles. As the feeling of sporty sound is somewhat less relevant in the stationary condition than under acceleration while driving [22], this study recorded sound under the wide open throttle (WOT) acceleration condition. As shown in Fig. 2.2, sound was recorded using the chassis dynamometer of a semi-anechoic chamber to minimize ambient noise. The tests were conducted with a dummy head from HEAD Acoustics placed in the passenger seat and two test members. One member was the driver, who pressed the gas pedal, and the other performed test operations and data acquisition. All driving tests were repeated five times to obtain reliable data. Each sound recording was approximately 10 s long and consisted of full-throttle data from second gear before changing to fifth gear. The four original samples obtained in this way were filtered to make various samples.

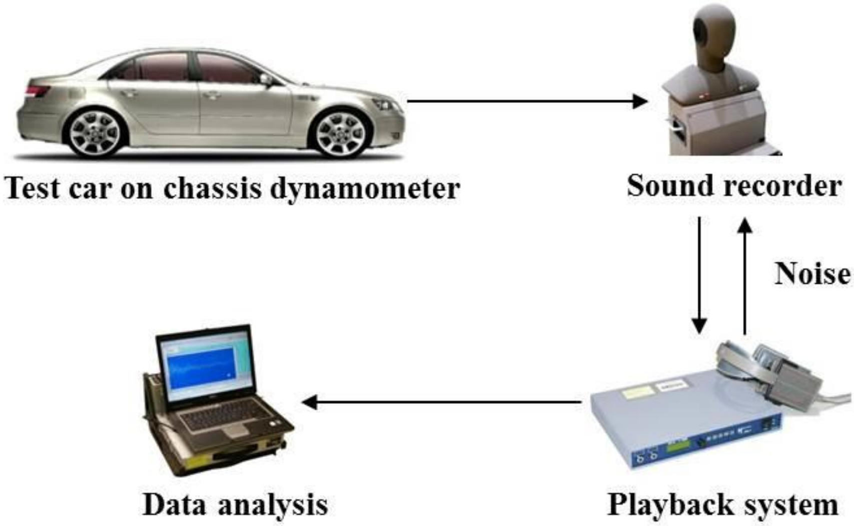


Figure 2.1 Data acquisition process for objective assessment.

Table 2.1 Specification of test vehicle including target vehicle and benchmarking vehicle.

Vehicle	Engine Type	Displacement	Fuel Type	Transmission
A (Target Vehicle)	I4	1.6 L	Gasoline	A/T
B	V6	3.5 L	Gasoline	A/T
C	V6	3.7 L	Gasoline	A/T
D	I4	2.0 L	Gasoline	A/T

Figure 2.2 Example of a driving test setup to obtain the interior sound of a vehicle using a dummy head.

2.2.2 Production of sound samples

Sporty engine sound is characterized by a range of variables, such as engine performance or shift timing. Because in this study, the variable that is controllable in a given environment is the feeling of sound, four recorded samples were prepared with frequency modulation by using several digital filters. First, after determining the frequency characteristics of the benchmarking vehicles, the target vehicle was synthesized to generate similar frequency spectra. Fig. 2.3 shows the examples. Fig. 2.3(a) shows the amplitudes of the recorded and modulated signals in the time domain. Fig. 2.3(b) shows the frequency characteristics of the target and benchmarking vehicles. Fig. 2.3(c) shows the frequencies of the target vehicle modulated using a band-pass filter to refer to the characteristics of the benchmarking vehicle. Next, the number of samples was increased by amplifying the frequency or order by considering elements affecting the sporty sound. The rationale is based on existing studies [11, 23-26]. The rumbling sound generated owing to half-order components, powerfulness that can be felt by variation of loudness, peak frequency originated from the explosive engine sound, and frequency ratio difference in the acceleration/deceleration area were emphasized. A parametric band-pass filter was used, and the degree of modulation was varied by at least 6 dB depending on the frequency band, such that people could feel the difference between samples. As a result, the juries heard and evaluated the varying sounds of the target vehicle. The color maps of Fig. 2.4 are examples of the fast Fourier transform (FFT) vs. time data for three samples. Fig. 2.4 (a) shows the spectrum of the original sound recorded before using the filter. Fig. 2.4 (b) shows a case in which the sound pressure of all frequencies was increased by applying the filter, and Fig. 2.4 (c) is a case in which only the sound pressure of the main order was increased. Since the variables for preparing the samples are further varied, an increase in the number of samples disturbs the concentration of the sound evaluators and inaccuracy occurs due to the increase in fatigue [27]. Thus, as a suitable number of samples is required for the jury test, we increased the number of samples from four to obtain a total of 13 samples.

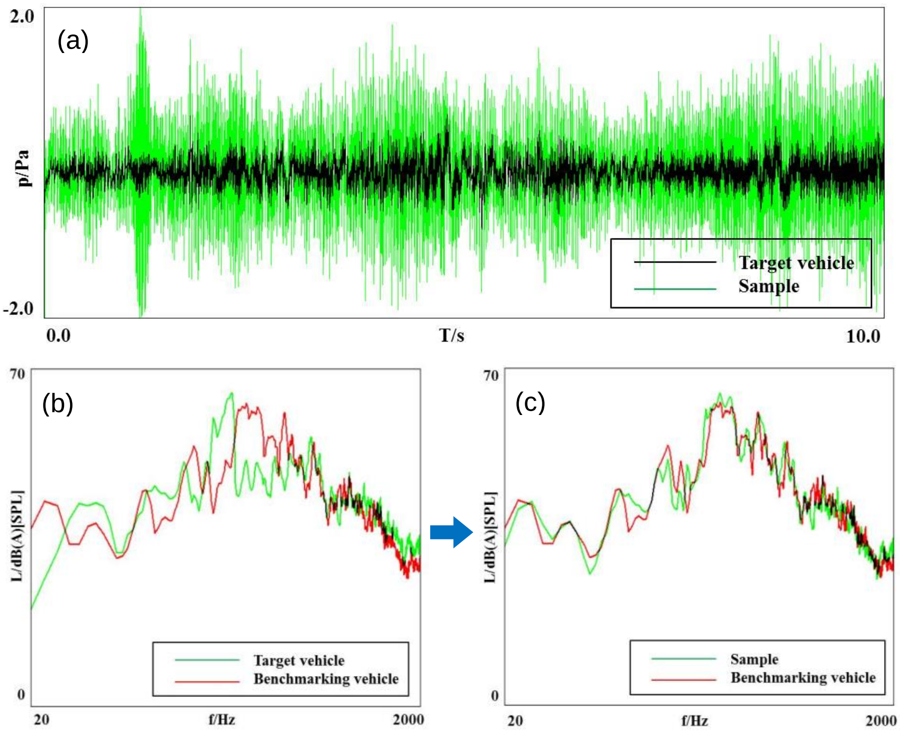


Figure 2.3 Time history and frequency spectra of the recorded and modulated signals: (a) time history of recorded target vehicle sound (black line) and modulated sound (green line), (b) frequency spectra of recorded target vehicle (green line) and benchmarking vehicle sound (red line), (c) frequency spectra of modulated target vehicle (green line) and recorded benchmarking vehicle sound (red line).

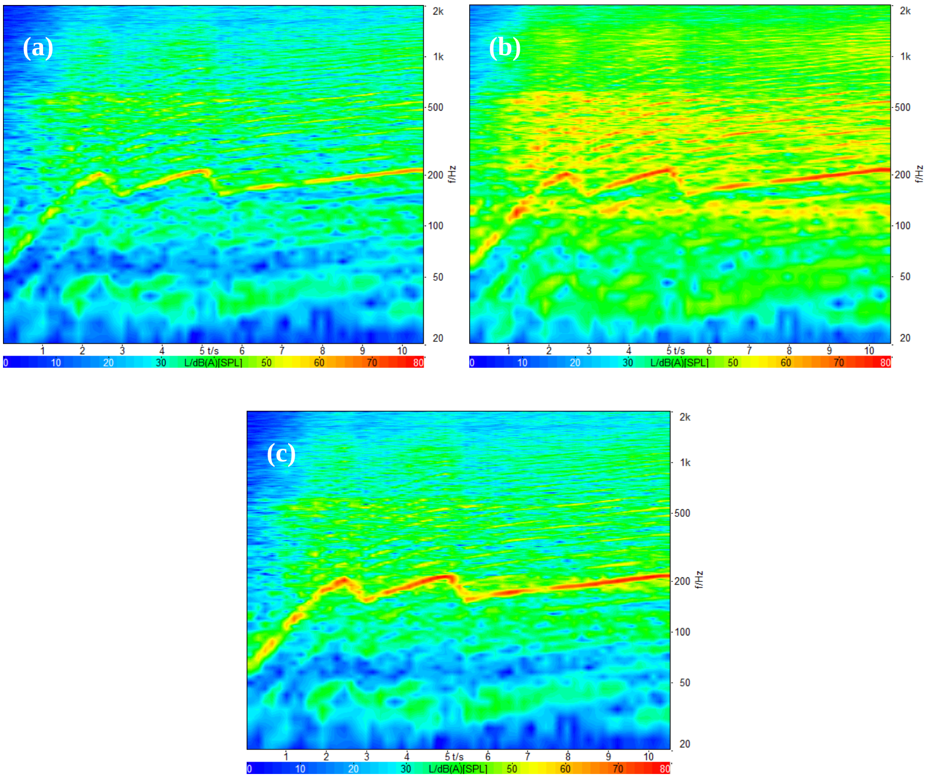


Figure 2.4 Example of a color map of the signal modulated through the recorded driving data and filters. (a) Original recorded sound before modulation. (b) Sound with increase in sound pressure of all frequencies within the audible frequency range. (c) Sound with increase in sound pressure of the second-order component that has a dominant effect on interior sound due to engine explosion.

2.2.3 Calculation of objective acoustic and psychoacoustic parameters

As a basic process in sound quality research, subjective concepts can be quantified by correlating the measurement data of recorded or produced sound with the results of jury tests. To accomplish this, the corresponding objective data are needed. Although sound pressure level (SPL) data can suffice when the goal is simply to reduce engine noise, it has limited use in determining people’s preferences regarding the sound’s “sportiness.” Therefore, this study not only measured the SPL of the 13 samples but also calculated the values of psychoacoustic parameters. We considered the typical sound quality metrics of loudness, sharpness, roughness, and tonality and calculated their values using HEAD Acoustics ArtemiS Version 8 with reference to ISO 532B and Aures’s model [28-37]. Table 2.2 shows the calculated results for each sample. The calculated values of the objective sound metrics were used as independent variables to analyze the correlation with human preference for sporty engine sounds and to further derive the sound quality index through multiple linear regression. In the following sections, the concepts of representative acoustic and psychoacoustic metrics used in this study are briefly described.

Table 2.2 Calculations of single values of acoustic and psychoacoustic parameters for each sample.

Sample	SPL_{OA} (dBA)	Loudness (sone)	Sharpness (acum)	Roughness (asper)	Tonality (tu)
1	62.90	15.70	1.18	1.56	0.257
2	70.30	26.80	1.47	2.18	0.236
3	73.60	24.40	1.11	1.89	0.203
4	75.90	35.50	1.42	2.53	0.256
5	66.60	18.50	1.14	1.56	0.281
6	69.60	21.80	1.43	1.92	0.189
7	67.10	22.50	1.59	2.09	0.225
8	65.70	18.60	1.56	1.83	0.184
9	71.20	24.20	1.02	1.84	0.264
10	66.50	16.40	1.07	1.58	0.207
11	62.90	18.20	1.70	1.81	0.226
12	74.10	23.90	0.95	1.82	0.209
13	75.00	31.10	1.15	2.19	0.256

2.2.3.1 Sound pressure level

Sound pressure level is a physical measure representing the level of sound pressure deviation relatively to a reference pressure. It is quantified using the ratio of measured pressure over a certain reference pressure represented on a decibel (dB) scale [38]. It is usually abbreviated as SPL or L_p, and is defined as

$$\mathrm{SPL} = 20\log\left(\frac{P_e}{P_{ref}}\right) \tag{2.1}$$

where P_e is the measured effective pressure amplitude and P_{ref} is the reference effective pressure amplitude. As the reference sound pressure is 20 μPa in air, a sound pressure level of 0 dB indicates a sound pressure of 20 μPa. SPL is often used to measure and identify the level of noise generated from machines. However, when the sound pressure is doubled, the SPL increases by 6 dB; but that sound can be audibly perceived by a person as an increase of 10 dB depending on the frequency. Therefore, all the psychoacoustic parameters must be considered because the difference in sound quality cannot be determined by sound pressure analysis alone [28-29].

2.2.3.2 Loudness

Loudness refers to the intensity of sound that is felt subjectively. It is a representative sound quality metric that indicates the difference in hearing as recognized through the human ear and is a basic factor for describing sharpness, roughness, and tonality. Zwicker proposed a loudness model that can analyze loudness regardless of the sound field by correcting the level between free and diffuse sound fields. It was certified by ISO 532B and the mathematical loudness model defined in this standard is as follows [28]:

$$N' = 0.08\left(\frac{E_{TQ}}{E_0}\right)^{0.23}\left[\left(0.5 + 0.5\frac{E}{E_{TQ}}\right)^{0.23} - 1\right] \qquad (2.2)$$

where N' is the specific loudness in sone/Bark, E_{TQ} is the excitation at threshold in quiet ambient, and E_0 is the excitation of the reference sound with an intensity of $I_0 = 10^{-12}\ \mathrm{W/m^2}$. The unit of loudness is sone, and 1 sone is a sine tone of frequency 1 kHz at a level of 40 dB. As shown below, the total loudness can be determined by obtaining the specific loudness from a stimulus according to each critical band and then integrating it for the critical band rate, as follows:

$$N = \int_0^{24\ \mathrm{Bark}} N'\, dz \tag{2.3}$$

where N is the total loudness of the sound and z is the critical band rate. However, in this study, loudness was calculated by referring to DIN 45631/A1 [30-32], which is based on the Zwicker model for time-variant sounds. As no international standard loudness measurement method for transient signals has yet been developed, the values may differ depending on the software application used by researchers.

2.2.3.3 Sharpness

Sharpness is a sound quality metric that represents the degree of sharpness of sound. Even if two sounds have the same loudness, the one with more high frequency components is audibly perceived as sharp. Sharpness is an important factor in the evaluation of vehicle engine sound [11]. Among the various sharpness calculation methods, this thesis used the Aures method [28, 33, 37]:

$$S = 0.11 \frac{\int_0^{24\ \mathrm{Bark}} N'\, \mathrm{g}(z) z dz}{\int_0^{24\ \mathrm{Bark}} N'\, dz} \tag{2.4}$$

where N' is the specific loudness and $g(z)$ is an additional factor that depends on critical band rate z. In other words, sharpness is determined by the frequency distribution of specific loudness. The unit of sharpness is acum, and 1 acum is defined as the sharpness of narrowband noise of 1 kHz with bandwidth less than 150 Hz and a level of 60 dB.

2.2.3.4 Roughness

Roughness is a sound quality metric for expressing the degree of roughness of sound. The frequency and amplitude modulation of sound can generate different senses such as fluctuation in addition to roughness, and this thesis recognized roughness, which has a high correlation with the sportiness of engine sound, as an important metric [11, 39]. The calculation method suggested by Aures was referenced for the roughness model [28, 34], which can be expressed as follows.

$$R = 0.3\frac{f_{mod}}{kHz}\int_0^{24\text{ Bark}}\frac{\Delta L(z)dz}{dB/Bark} \tag{2.5}$$

where f_{mod} is the frequency of modulation and $\Delta L(z)$ is the temporal masking depth. The unit of roughness is asper, and 1 asper is a sine tone of 1 kHz with a level of 60 dB, 100% amplitude-modulated at a frequency of 70 Hz.

2.2.3.5 Tonality

Tonality is a measure of the ratio of tonal components in the spectrum of signals. It is a sound quality metric that quantifies the importance of single-frequency sounds included in a sound. In other words, the higher the number of tones included in a sound, the higher is the tonality value. The unit of tonality is tu, and 1 tu is a sine tone of frequency 1 kHz at a level of 60 dB. Tonality is calculated based on the loudness model of ISO 532B. The method for calculating tonality has been well-established by Aures and Terhardt [28, 33, 35]. Gonzalez et al. considered tonality as a major parameter when conducting a study on vehicle engine sound quality for active noise control (ANC) [40]. Tonality is a frequently measured metric in analyzing a vehicle’s powertrain sound [41]. Therefore, this thesis also examined tonality as a major variable.

2.3 Subjective evaluation of sound quality

2.3.1 Semantic differential method and pre-test

The semantic differential method is used by the evaluator himself or herself to absolutely evaluate the subjective feeling of a specific sound on a scale by using a variety of emotional vocabularies. The method is highly suitable for displaying the characteristics of the sound being evaluated because it is relatively easy to obtain a large amount of data. Thus, we chose to use the semantic differential method devised by Osgood [42], which facilitates analyzing what a concept (such as "sportiness") means to people. And the method helps to specify the abstract image an individual has about sportiness and to identify the adjectives that best describe the engine sound being targeted. Before selecting adjective pairs for the final evaluation, 503 adjective pairs were first listed in alphabetical order, among which 25 adjective pairs related to sportiness were primarily selected [22, 42-43]. Next, through the pre-test, 19 evaluators were asked to select the adjectives that best describe the sporty sound after hearing the sound of 12 sports cars. Subsequently, seven adjective pairs were selected by identifying the frequency of selection excluding synonyms. The adjective pairs were

“Strong–Weak,” “Sharp–Soft,” “Dynamic–Static,” “Overwhelming–Comfortable,” “Stereophonic–Simple,” “Thick–Thin,” and “Clear–Ambiguous.” The preference for each evaluation item was assessed as “Sporty–Not Sporty.” The questionnaire that was used to discover the relationship with sportiness by using the semantic differential method is provided in Table 2.3.

Table 2.3 Jury test questionnaires to understand the relationship between adjective pairs and preferences.

Strong	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Weak**
Sharp	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Soft**
Dynamic	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Static**
Overwhelming	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Comfortable**
Stereophonic	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Simple**
Thick	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Thin**
Clear	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Ambiguous**
Sporty (Preference)	Extremely □	Very □	Somewhat □	Neither □	Somewhat □	Very □	Extremely □	**Not Sporty**

2.3.2 Jury testing

The evaluation was conducted in a semi-anechoic chamber to minimize ambient noise (the same conditions under which the vehicles were recorded), and the PEQ V playback system of HEAD Acoustics was used. To investigate the sporty sound preference, the jury comprised a total of 23 participants: 20 males and 3 females, with a mean age of 27.4 years and no hearing impairments (Fig. 2.5). The participants were all unbiased non-experts and were fully informed of the purpose and method of the jury test through pre-training. Each sample was played five times; the playback order was random to eliminate any effects between samples when listening.

Box plots were produced by excluding outliers consisting of singular values. Fig. 2.6 shows a box plot for the “sharp-soft” evaluation item among the seven adjective pairs. The abscissa represents the samples, and the ordinate represents the scores for each sample. The red circles indicate singular values and the numbers represent the number of evaluators. In this way, every evaluation item was tested for consistency; singular values and the data of evaluators that did not satisfy the criteria were excluded. According to Otto et al., inconsistent evaluation should be carefully considered because it directly affects the data reliability, and their study allowed the inclusion of data when the data reliability was higher than 75% on average [27]. Accordingly, in this study, of the 23 evaluators, the three who showed dissimilar responses to the same sample were deemed to be inconsistent and were removed. More specifically, three identical samples were additionally randomized for evaluation together and accepted in the case when the scores did not differ by more than one point. Consequently, the final dataset consisted of data from 20 evaluators.

Fig. 2.7 shows the results of the jury test. For improved visibility, only six among the 13 samples with a large difference in their scores are shown, and the remaining samples with similar patterns are omitted. The radar graph provides an approximate idea of the relationship between sportiness preferences and adjectives. The sample with the highest sportiness score is no. 13 (represented by a red dotted line), whereas the sample with the lowest score is no. 5 (represented by a blue dashed line). The results show that the pairs strong, dynamic, overwhelming, stereophonic, and thick tend to follow the trend as the sportiness score increases and decreases based on the results of samples no. 13 and no. 5. However, the pair consisting of sharp and clear does not follow that tendency. The results predict that the sportiness is influenced by the characteristics of strength and richness of sound. It can be predicted that the effect of sharpness on sportiness will be relatively small.

Factor analysis was carried out with the aim of obtaining a basis for the results and to define sportiness more precisely.

Figure 2.5 Jury test environment

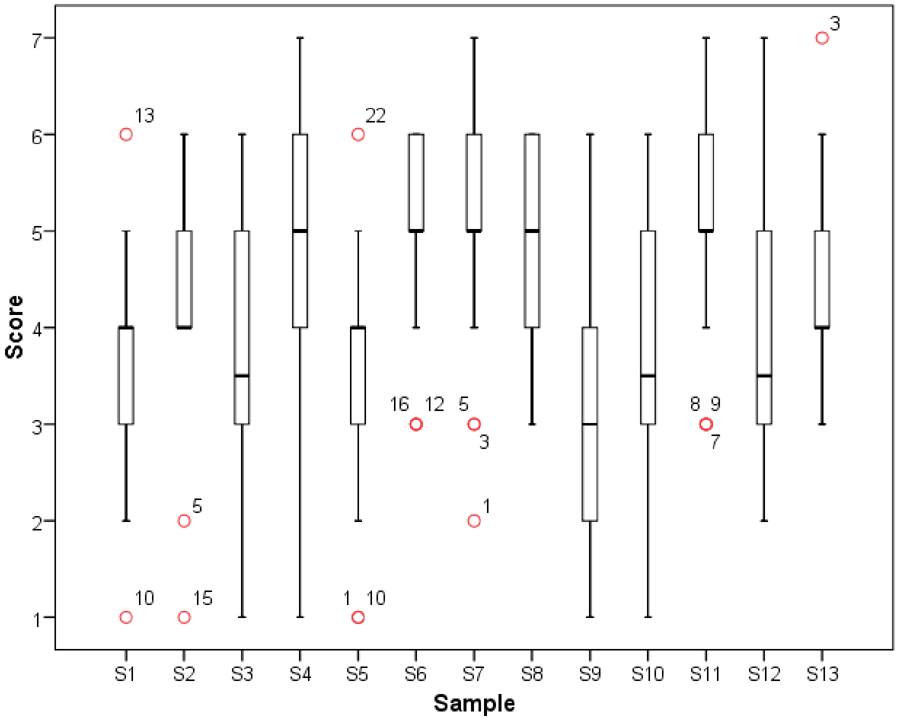


Figure 2.6 Box plot for the “sharp-soft” evaluation item.

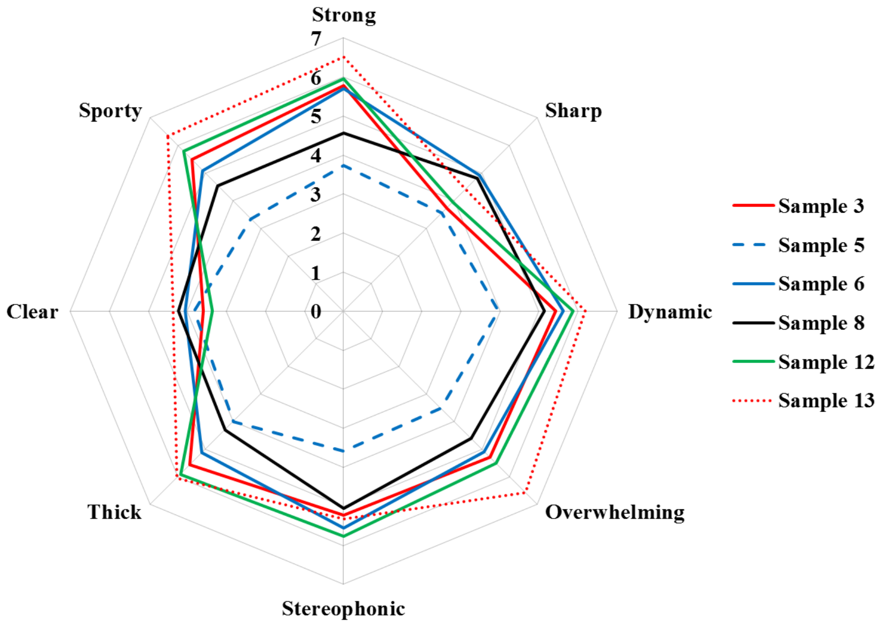


Figure 2.7 Subjective evaluation results to confirm the relevance between sporty preferences and adjectives.

CHAPTER 3

DEVELOPMENT OF EVALUATION INDEX OF SPORTY ENGINE SOUND : USING FACTOR ANALYSIS

3.1 Introduction

This chapter describes the process of developing a regression model for sportiness from the objective and subjective evaluation results in Chapter 2. In this process, factor analysis is used to obtain better results when quantifying sportiness and to emphasize the necessity of factor analysis.

3.2 Factor analysis

Based on the results of the jury test obtained by using the aforementioned semantic differential method, factor analysis was conducted to collect common variables with a high association between the words used in the evaluation and to further reduce them to a smaller number of representative factors. The objective of the factor analysis is to determine how many factors affect the data of various variables, and a subsequent analysis such as regression analysis can produce more accurate results through new latent variables rather than variables of the original data [44-45].

In order to perform a regression analysis based on the results of the factor analysis, a factor score matrix corresponding to the number of extracted factors is required. The first step to construct the factor score matrix is the determination of the correlation matrix. The correlation matrix is the matrix consisting of correlation coefficients of the observed variables. Next, the factor loading matrix is calculated by decomposing the correlation matrix, and the eigenvalues are identified in the process to determine the number of latent factors. If necessary, the researcher can rotate the axis of the factors around the origin, this process is carried out to facilitate the interpretation of the data, using two methods: orthogonal rotation or oblique rotation. Finally, by matching the dimension of the calculated factor loading matrix and multiplying by the inverse matrix, the factor score matrix can be calculated. The mathematical model of the factor analysis is expressed as follows [46]:

$$z_j = a_{j1}F_1 + a_{j2}F_2 + \cdots + a_{ji}F_i + d_jU_j \tag{3.1}$$

z_j represent the n observed values where j = 1, 2, 3,…, n. F_i represent the m common factors where i = 1, 2, 3,…, m. a_{ji} represent the $n \times m$ factor loadings. And d_jU_j are unique factors, which represent unobserved stochastic error terms. Eq. (3.2) is expressed in matrix [47],

$$[\mathbf{Z}] = [\mathbf{F}][\mathbf{L}]^{\mathbf{T}} \tag{3.2}$$

where $[\mathbf{Z}]$ denotes the original data matrix, $[\mathbf{L}]$ is the factor loading matrix, and $[\mathbf{F}]$ is the factor score matrix. The factor score matrix can be calculated by solving the Eq. (3.2) for $[\mathbf{F}]$:

$$[\mathbf{F}] = [\mathbf{Z}][\mathbf{L}]([\mathbf{L}]^{\mathbf{T}}[\mathbf{L}])^{-1} \tag{3.3}$$

Thus, based on the calculation process shown above, the study confirmed the results of the factor analysis by using the statistical program SPSS to discover new factors that can represent each group by identifying the correlations of adjective pairs and grouping the variables showing similar characteristics. Principle components analysis was applied as a factor extraction method and the result was further analyzed by using a correlation matrix. In order to solve the problem of multicollinearity when conducting regression analysis, factor scores of two factors with an eigenvalue greater than 1 were extracted through factorial rotation using varimax rotation one of many methods of orthogonal rotation. Fig. 3.1 shows a scree plot to show the eigenvalue of each factor visually. As shown in the Fig. 3.1, the eigenvalues of factor 1 and factor 2 are 4.516 and 2.028, respectively, and the total percent variance is 93.482% with the accumulation of 64.511 and 28.971. The value means that the two extracted factors have an explanatory power exceeding 93% of the total variance. The validity and reliability of the factor analysis should be secured before using the results of the factor analysis. First, a reliability analysis was conducted to confirm whether respondents who participated in the evaluation provided responses with reliability. The reliability was confirmed by the Cronbach's coefficient α, which is determined to be reliable if α is greater than 0.7 [48].

The reliability analysis was twice conducted before and after the factor analysis. In the former analysis, the α value was found to be 0.889, testing whether the entire evaluation items were well composed. The latter analysis tested whether common factors can be extracted by averaging the grouped evaluation items based on the similarity. The values for each factor are 0.964 and 0.872, respectively, showing a high level of reliability. Furthermore, in order to validate the results of the factor analysis, it is necessary to confirm whether the conditions of KMO (Kaiser-Meyer-Olkin) and Bartlett's test of sphericity are satisfied. The KMO measure is a measure of whether the correlation between variables is well explained by other variables. Typically, the KMO measure judges whether a factor analysis is appropriate with a threshold of 0.5 or more. Bartlett's test of sphericity is to determine if the factor analysis is appropriate by checking if the p-value is less than 0.05 [45]. The results are shown in Table 3.1, and the validity of the factor analysis was secured by the KMO value of 0.675 and the significance of 0.000. Table 3.2 shows the rotated factor matrix, which was obtained by the factor analysis, and Fig. 3.2 is the corresponding factor plot in two-dimensional space. Although each component was sorted in decreasing order of size, as shown in Table 3.2, the seven adjective pairs are "strong-weak," "overwhelming-comfortable," "dynamic-static," "stereophonic-simple," and "thick-thin," which are classified as factor 1; "sharp-soft," and "clear-ambiguous," which are classified as factor 2. Based on the meaning of each adjective, factor 1 was named "sonorousness" representing a feeling of powerfulness and dynamics; and factor 2 was named "shrillness" showing a characteristic of sharpness. The naming means that in describing sportiness, the characteristics that people commonly feel about sportiness are defined as "sonorousness" and "shrillness", and that a small number of factors can provide sufficient explanatory power. Moreover, as previously predicted in Fig. 2.7, "sharp-soft," and "clear-ambiguous" have different characteristics from adjectives belonging to factor 1, and the eigenvalues and percent variances of factor 1 and factor 2 could confirm that the influence of factor 1 on sportiness was high and that the contribution of factor 2 was relatively small. When people produce an image of sportiness, they think about images such as "sonorousness" and "shrillness," which can be interpreted to mean that an image that expresses dynamics and strength is more important than an image of sharpness. Subsequently, by using the factor scores of two factors based on the factor loading values derived from this factor analysis, the regression analysis is performed to specifically segment the concept of sportiness and objectively quantify the concept. As a result, this study is aimed to confirm that we can derive a more effective performance model by minimizing the inclusion of unnecessary variables through factor analysis than the results obtained by simple regression analysis of sportiness with multiple variables.

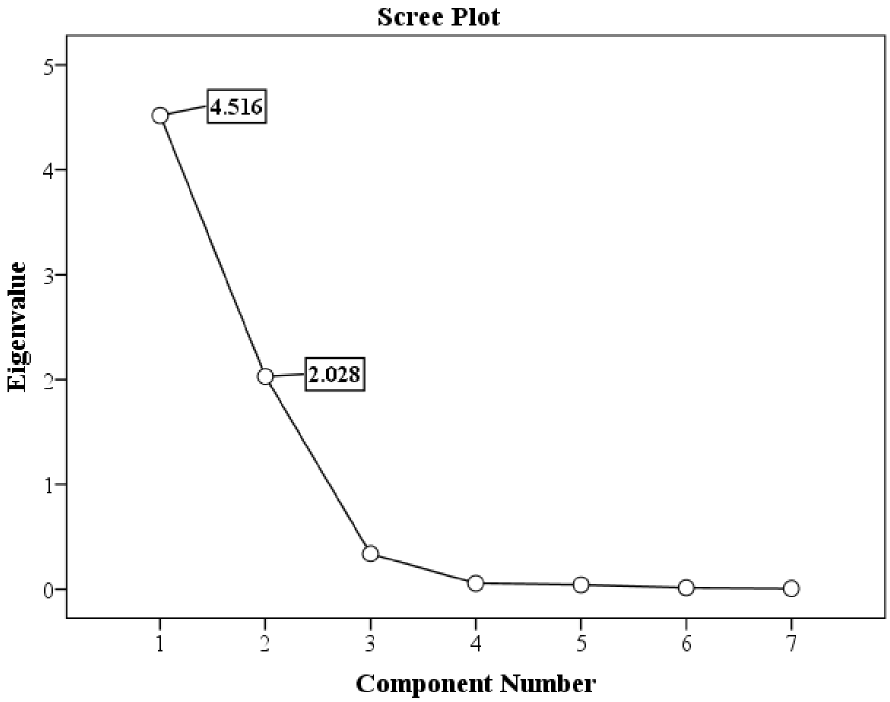


Figure 3.1 Scree plot to identify eigenvalues.

Table 3.1 KMO and Bartlett's Test to confirm the validity of the factor analysis results.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.675
Bartlett's Test of Sphericity	Approx. Chi-Square	126.422
	df	21
	Significance	0.000

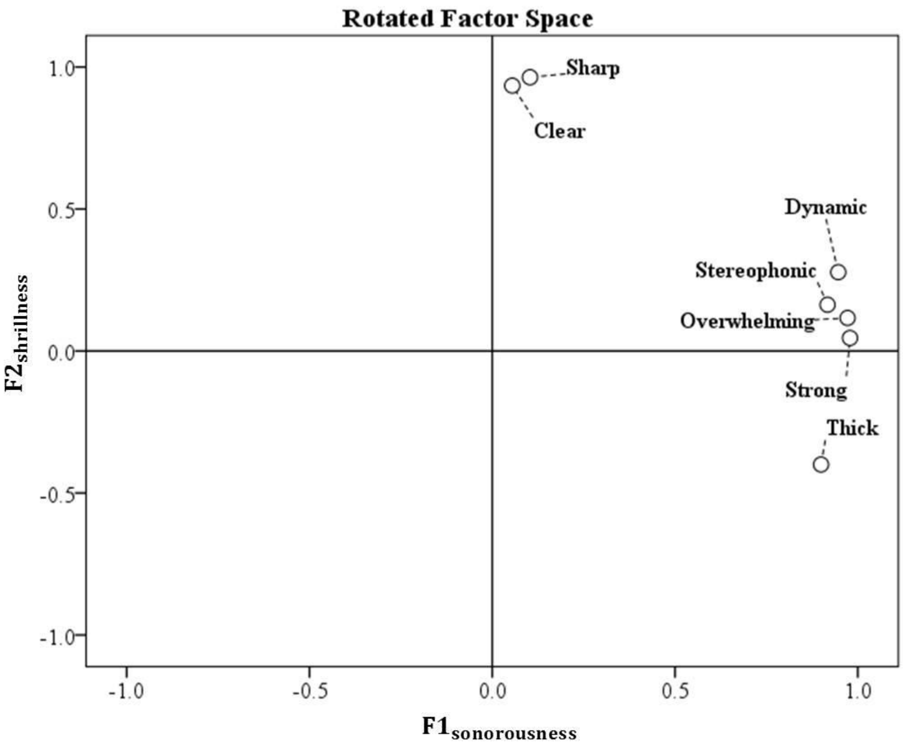


Figure 3.2 Factor plot in a two-dimensional space to visualize the components of two factors.

Table 3.2 Factor matrix showing the factor loadings after varimax rotation and Cronbach alpha.

Rotated Factor Matrix				
	Factor		Cronbach Alpha	
	1	2		
Strong-Weak	**0.979**	0.046	0.964	0.889
Overwhelming-Comfortable	**0.972**	0.116		
Dynamic-Static	**0.946**	0.278		
Stereophonic-Simple	**0.917**	0.163		
Thick-Thin	**0.899**	-0.400		
Sharp-Soft	0.103	**0.964**	0.872	
Clear-Ambiguous	0.055	**0.934**		

3.3 Regression analysis

3.3.1 Multiple linear regression

Multiple linear regression analysis is a statistical technique that analyzes the effect between variables based on linear regression with one dependent variable and multiple independent variables. The analysis is useful for testing the validity of a hypothesis, and thereby used as a tool to predict the value of the dependent variable. Unlike correlation analysis, which simply compares linear associations between two variables, the regression analysis must find regression equations which can best explain the linearity by proving causality between correlated variables. Because this study was aimed to develop a sound quality index for the sportiness of the engine sound, the study was conducted to derive the optimal regression equation based on regression analysis theory. Typically, multiple linear regression is expressed as described below [49-50]:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_i X_i + \varepsilon_i \tag{3.4}$$

where i = 1, 2, 3,…, n. In the linear regression model, Y_i is a dependent variable, sportiness, showing the influences by factors, β_i is the coefficient estimated for the independent variable, X_i is an independent variable corresponding to factor 1 or factor 2 obtained through factor analysis. Accordingly, the final regression equation is derived by estimating an initial regression equation between sportiness and factors, and by further setting the factors as dependent variables and related sound metrics as independent variables. Finally, the relationship between sportiness and sound metrics can be derived by substituting the result into the equation of sportiness and factors.

3.3.2 Development of a sound quality index for sportiness

The sound quality index for sportiness is derived from the subjective evaluation based on the results of the jury test on preferences and images of adjective pairs previously obtained as well as objective evaluation results based on the actual measurement data of the vehicle. The most basic task of multiple regression analysis is to find the beta regression coefficient. Thus, SPSS was used for the data processing to obtain the coefficient, as in the factor analysis, and the confidence level was allowed by 90% in obtaining the regression equation. As a method of estimation, to explain the dependent variable, a stepwise method is used to obtain a regression equation consisting of only variables whose influence is at least above a certain level. The results are shown in Eqs. (3.5)-(3.8):

$$\begin{aligned} Sportiness_{\mathrm{FA}} = 4.958 + 0.923 \times F1_{\mathrm{sonorousness}} \\ + 0.121 \times F2_{\mathrm{shrillness}} \end{aligned} \tag{3.5}$$

Eq. (3.5) is the regression equation obtained by regression analysis based on the results of the factor analysis, and the subscript of the dependent variable is the factor analysis. $Sportiness_{\mathrm{FA}}$ represents preference for sportiness, $F1_{\text{sonorousness}}$ and $F2_{\text{shrillness}}$ imply factors to express preference for sportiness. One of the important considerations in multiple regression analysis is multicollinearity. Multicollinearity refers to a phenomenon where it is difficult to grasp the influence of each of these variables when the correlation between variables is high. When the factor analysis is performed, independent variables, which are completely independent between variables, are derived. Thus, the issue of multicollinearity can be resolved. According to the results, the sportiness that people perceive means that the engine sounds sporty when it sounds sonorous and shrill. Furthermore, the standardized regression coefficients for these variables are 0.967 and 0.127, respectively, specifically showing that the perception is affected by sonorousness to a larger extent. Moreover, to evaluate how well a regression equation explains the data, the degree of validity of the regression model is determined by R^2 or R^2_{adjust}, where the values are 0.952 and 0.943, respectively, showing high explanatory power. The p-value of each variable is 0.000, and 0.097, respectively, which is a significant result.

$$F1_{\text{sonorousness}} = -12.979 + 0.157 \times \text{SPL}_{\text{OA}} + 1.088 \times \text{Roughness} \tag{3.6}$$

$$F2_{\text{shrillness}} = -4.829 + 3.739 \times \text{Sharpness} \tag{3.7}$$

Eqs. (3.6)-(3.7) show the causal relationships between the sound metrics related to each factor. First, in Eq. (3.6), the dependent variable has a positive correlation to the magnitude of sound and degree of roughness. R^2 and R^2_{adjust} are 0.866 and 0.839, respectively, and the p-values of the variables are 0.001 and 0.075, respectively. Eq. (3.6) shows that the independent variable well explains the dependent variable. In the same manner, $F2_{\text{shrillness}}$ of Eq. (3.7) is affected by sharpness, and R^2 and R^2_{adjust} are 0.842, and 0.828, respectively, with a high explanatory power. SPL_{OA} is the A-weighted sound pressure level, which represents the overall value of the audible frequency range, and roughness and sharpness are the single values that were calculated by using Aures's model. By finally combining Eqs. (3.6)-(3.7) with Eq. (3.5), the relationship between sportiness and metrics, Eq. (3.8), can be obtained, which is a relationship between sportiness and metrics.

$$\begin{aligned} Sportiness_{\text{FA}} = -7.606 + 0.145 \times \text{SPL}_{\text{OA}} + 1.004 \\ \times \text{Roughness} + 0.452 \times \text{Sharpness} \end{aligned} \tag{3.8}$$

As shown in Eq. (3.8), the sound quality index obtained from the factor analysis means that the image of the sportiness experienced by people can be expressed by the degrees of roughness and sharpness of the sound including the magnitude of the sound. Each contribution can be revealed through the standardized regression coefficient, and the standardized regression coefficient shows a degree of contribution in order of SPL_{OA}, roughness, and sharpness with the values of 0.676, 0.296, and 0.116, respectively. Eq. (3.8) was obtained from Eq. (3.5), and the contribution of each independent variable follows that in Eq. (3.5).

Typically, regression analysis itself is a powerful tool for estimating the causal relationship between variables. Thus, many studies have been conducted to develop a linearized index with only regression analysis in various engineering fields [13, 51-54]. Therefore, this study emphasizes the effect and necessity of factor analysis by comparing the results of regression analysis without additional factor analysis.

$$Sportiness_{\mathrm{MLR}} = -11.756 + 0.218 \times \mathrm{SPL_{OA}} + 1.232 \times \mathrm{Sharpness} \tag{3.9}$$

Eq. (3.9) is the result of the regression analysis to confirm the causal relationship between sportiness and sound metrics that have not undergone factor analysis, and the subscript of the dependent variable is written as multiple linear regression to differentiate it from Eq. (3.8). SPL_{OA} and sharpness were selected as independent variables, and R^2 and R^2_{adjust} in the regression equation are 0.880, and 0.856, respectively. The p-values are 0.000 and 0.024, respectively. The results of Eq. (3.9) further show that the independent variables can sufficiently explain the sportiness, as previously shown in the results obtained with Eq. (3.8). The standardized regression coefficient showed that the effect of roughness was excluded, which is different from Eq. (3.8), and that the effect of sharpness was increased. These differences between Eqs. (3.8)-(3.9) can be explained by a re-performance of the objective and subjective evaluations with a new sample set to determine which regression equation is more effective. The results of the derived regression equations are summarized in Table 3.3.

Table 3.3 Summary of the results of the derived regression equations.

Dependent variable	Independent variable	β_i	Standardized coefficient	t	p	R^2	R^2_{adjust}
	Constant	4.958					
$Sportiness_{\mathrm{FA}}$	$F1_{\mathrm{sonorousness}}$	0.923	0.967	13.980	0.000	0.952	0.943
	$F2_{\mathrm{shrillness}}$	0.121	0.127	1.833	0.097		
	Constant	-12.979					
$F1_{\mathrm{sonorousness}}$	$\mathrm{SPL_{OA}}$	0.157	0.699	4.527	0.001	0.866	0.839
	Roughness	1.088	0.306	1.984	0.075		
$F2_{\mathrm{shrillness}}$	Constant	-4.829				0.842	0.828
	Sharpness	3.739	0.918	7.656	0.000		
	Constant	-11.756					
$Sportiness_{\mathrm{MLR}}$	$\mathrm{SPL_{OA}}$	0.218	1.017	8.518	0.000	0.880	0.856
	Sharpness	1.232	0.317	2.655	0.024		

3.4 Validation

It is necessary to check the reliability of the derived regression equation and the extent to which the equation can accurately describe the sportiness. Thus, eight new samples were prepared, the jury test was performed, the sound metrics were calculated, and the results were confirmed. The new samples underwent level modulation by using an order filter. The samples were prepared by considering the main order, half order, and harmonic components of the engine in the operating area of the vehicle. Fig. 3.3 shows the difference between the recorded sound of the target vehicle (green line) and the sample fabricated through order amplification (red line), regarding the second-order components corresponding to the main order of a 4-cylinder engine. To perform the subjective evaluation, 15 evaluators (normal hearing subjects; 15 males aged 30.2 years on average) were asked to rate the sportiness of the eight samples by using the seven-point scale. The objective evaluation was performed, as in Sec. 2, by calculating the values of SPL_{OA}, roughness, and sharpness, which were combined with the developed sound quality index to obtain the sportiness scores. A comparison of the correlation in the sportiness scores from the jury test and the sound quality index can show how the derived regression equation can represent the responses by the evaluators. Furthermore, the correlation coefficients from the scores estimated from Eqs. (3.8)-(3.9) could determine which equation explains the sportiness more accurately. The results are presented in Table 3.4.

Fig. 3.4(a) shows the correlation between the scores of Eq. (3.8) and the subjective evaluation which was obtained after the factor analysis was conducted. The correlation coefficient R showed a strong positive correlation with a value of 0.923, which means that the result can be appropriately used as an index representing sportiness. Fig. 3.4(b) shows the correlation between the scores of Eq. (3.9), which were obtained without factor analysis, and of the subjective evaluation. The correlation coefficient R is high with a value of 0.889, indicating the linearity is weaker than that in Eq. (3.8). As shown in Fig. 3.4, although both Eqs. (3.8)-(3.9) are indices with high reliability, the index with the factor analysis produces a more accurate result than that without the analysis when using factor analysis.

Table 3.4 Jury test score, indices score, and correlation coefficient of new samples for validation.

	Jury Test	*Sportiness*$_{\mathrm{FA}}$	*Sportiness*$_{\mathrm{MLR}}$
Sample 1	3.463	4.754	4.832
Sample 2	5.074	5.172	5.212
Sample 3	5.321	5.373	5.785
Sample 4	5.970	5.656	5.928
Sample 5	3.546	4.860	5.050
Sample 6	4.111	4.862	4.963
Sample 7	4.157	4.971	5.016
Sample 8	4.796	4.913	5.125
Correlation coefficient *R*		**0.923**	**0.889**

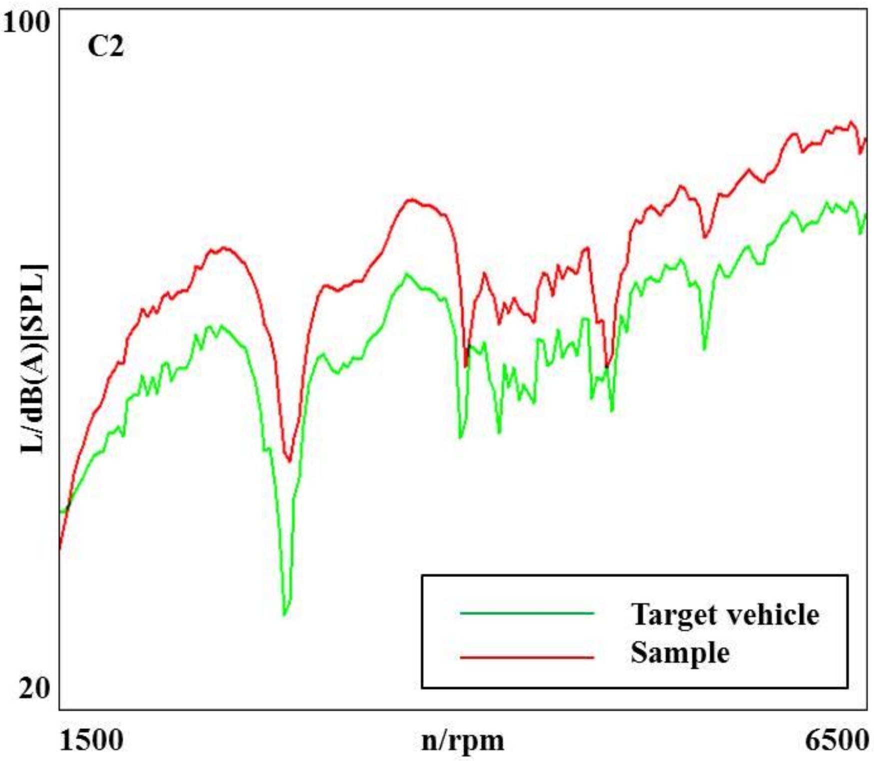
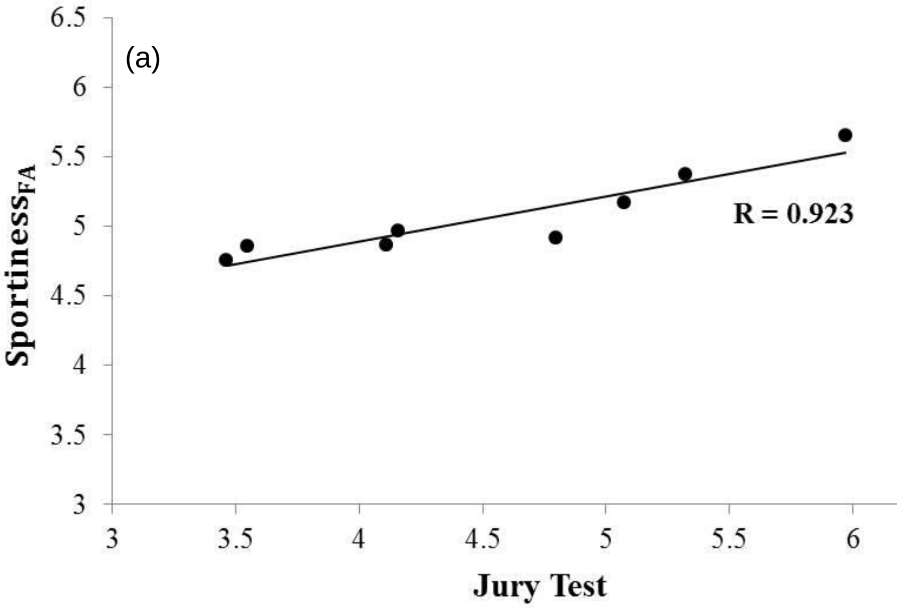


Figure 3.3 Second-order components of the recorded target vehicle sound (green line) and the modulated sound (red line).



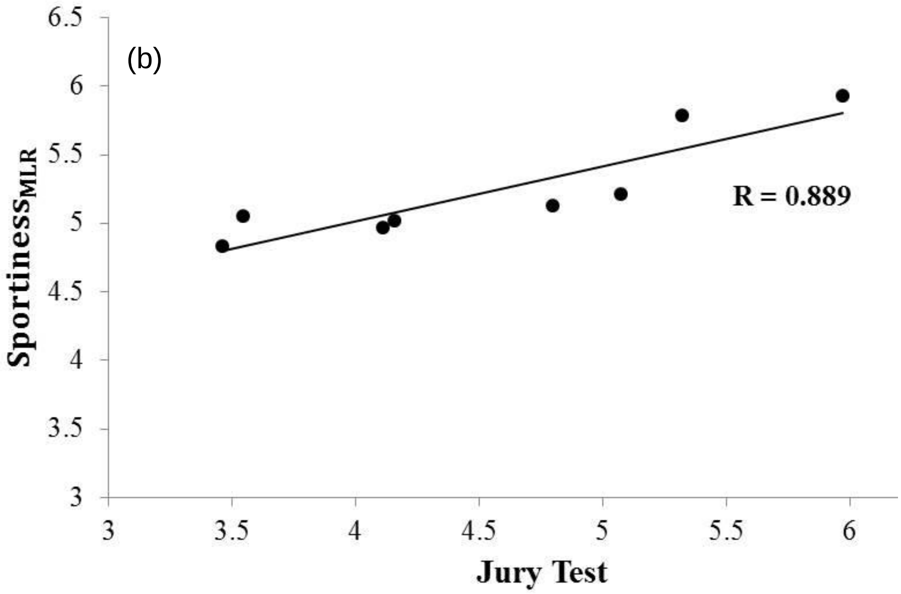


Figure 3.4 Correlation between subjective rating and derived indices: (a) $\mathit{Sportiness}_{\mathrm{FA}}$ and (b) $\mathit{Sportiness}_{\mathrm{MLR}}$.

3.5 Summary

In Chapter 3, based on the results of the sound quality evaluation of the vehicle engine sportiness in Chapter 2, a sound quality study was conducted to determine the commonly perceived feeling toward and to objectively define the sportiness of engine sound as a subjective concept. First, the engine sounds of 4 vehicles were recorded and 13 samples were created by using various filters based on the recorded data. Sound metrics with a significant relationship to the engine sound were selected to calculate the corresponding values for each sample. In the subjective evaluation, the semantic differential method was used to segment the meaning of sportiness into easy-to-understand adjectives, and to link the preferences of sportiness with the meaning of adjectives. Twenty-three evaluators participated, and the factor analysis was conducted by using their responses. The results of the factor analysis showed that the various adjective pairs could be classified into "sonorousness" and "shrillness," both of which emotions people commonly experience in relation with sportiness, and these two factors can explain 93% of the total variance. Based on the results of subjective evaluation and objective measurement, multiple linear regression analysis was used to prove the causal relationship between sportiness preference and related sound metrics. Finally, a sound quality index capable of explaining the sportiness of the engine sound was developed. The developed index has a positive correlation with $\mathrm{SPL_{OA}}$, roughness, and sharpness, which means that the sportiness can be estimated by using these three metrics. The results further mean that the image of the sportiness people experience can be expressed by the degrees of roughness and sharpness of the sound including the magnitude of the sound. The sportiness index obtained by factor analysis was tested by using Eq. (3.8) to assess the reliability of the new sample group. As a result, the validity of the equation was proved by showing very high correlation with subjective evaluation. Furthermore, a comparison of the index (Eq. (3.9)) from the regression analysis alone and correlation coefficient confirmed that $Sportiness_{\mathrm{FA}}$ is a more appropriate index. Ultimately, by objectively quantifying the subjective feeling of sportiness, the study could obtain more efficient and more accurate results by using factor analysis to develop a sound quality index.

CHAPTER 4

NEW APPROACH TO DEVELOPMENT OF EVALUATION INDEX OF SPORTY ENGINE SOUND : USING K-MEANS CLUSTER ANALYSIS

4.1 Introduction

This chapter describes the process of searching for a method to develop an index that acknowledges the opinion of minority groups regardless of gender or age, under the assumption that the sportiness index obtained in Chapter 3 reflects the opinion of the majority but does not describe that of relevant minority groups. Therefore, the effect on gender differences [55] was not taken into account in determining preferences. And the process of further subdividing the meaning of sporty engine sound based on this index is also described. By assessing the evaluators' comments and preference tendencies in the results of the jury test as mentioned in chapter 2, we found that the participants could be divided into two groups: one whose concept of "sportiness" is a feeling of rich and heavy bass, and one whose concept of "sportiness" is a feeling of speed due to high-frequency components, such as the sound of a Formula One. Thus, this chapter applied cluster analysis to develop sound quality indices that can also consider the sounds demanded by minority groups of customers, which are often not reflected because of the influence of the majority.

Consequently, a new evaluation model was developed by classifying what the evaluators think by using K-means clustering and performing the research detailed in Chapters 2 and 3.

4.2 Statistical analysis

4.2.1 K-means cluster analysis

Cluster analysis is a multivariate analysis technique in which the variables are measured for the observed objects, after which the values of the observed variables are used to judge the degree of similarity between the objects to classify them; they are then clustered by distance. This facilitates understanding the classified groups and enables their efficient use. Fig. 4.1 shows a brief cluster analysis procedure. In this study, the variables correspond to the engine sound samples, and the observation targets are evaluators, who have different feelings about the variables. As mentioned in Section 2.3.2, when the abstract concept "sportiness" is used in an objective equation, the concept is expressed differently according to the tastes of the different individuals. As a result, cluster analysis is needed to reflect the opinions of minority groups as well. K-means clustering was performed for this purpose.

Cluster analysis methods are divided into hierarchical and nonhierarchical; the K-means clustering method is typical of the latter type. In this method, the number of clusters K is determined, and the observed objects nearest to the center of the initially set cluster are included. The method is also a type of unsupervised learning used to study the structure of unlabeled data, in which the specific response variables are unknown. In K-means clustering, the dependence of the result can vary because the number of clusters K is determined by the user; after hierarchical methods such as Ward's clustering are performed, methods of comparison using K-means clustering are applied [16]. This study, however, focused on setting the desired results and validating their meaningfulness. Factor analysis, which will be described in Section 4.2.2, provides a rough estimate of the number of clusters based on the number of principal components. As a result of this analysis, we set the number of initial clusters K to 2 without considering the effect of the optimal number of clusters. The K-means clustering algorithm is clear and not very complex; it follows the following procedure [56-57].

Step 1. Determine the initial number of clusters K.

Step 2. Calculate the centroid for each variable corresponding to the determined number of clusters.

Step 3. Calculate the distance between each observed object and the initial centroid, and assign the observed object to the cluster closest to the result.

Step 4. Set a new centroid based on the mean of the variables in the group.

Step 5. Repeat Step 3 using the new centroid until the observed objects are not relocated to another group.

This can be expressed mathematically as follows [58]. First, the initial centroid $\mathbf{m}^{(k)}$ is set to a random value, and the initial estimated value identifying the cluster $k^{(n)}$ to which the point $\mathbf{x}^{(n)}$ belongs is $\hat{k}^{(n)}$. This is expressed by Eq. (4.1):

$$\hat{k}^{(n)} = \text{argmin}_k\{d\left(\mathbf{m}^{(k)}, \mathbf{x}^{(n)}\right)\} \tag{4.1}$$

where $d(\mathbf{m}^{(k)}, \mathbf{x}^{(n)})$ indicates the distance between the data point $\mathbf{x}^{(n)}$ and the centroid $\mathbf{m}^{(k)}$ and is typically calculated using Euclidean distance. Argmin represents the minimum distance value for arranging each data point to be closer to the centroid of a cluster. Eq. (4.2) is the equation for updating the position of the centroid.

$$\mathbf{m}^{(k)} = \frac{\sum_n r_k^{(n)} \mathbf{x}^{(n)}}{R^{(k)}} \tag{4.2}$$

$$R^{(k)} = \sum_n r_k^{(n)} \tag{4.3}$$

$r_k^{(n)}$ is an indicator variable that is 1 when $\hat{k}^{(n)} = k$ and 0 otherwise. The new centroid is calculated from the mean of the data, and $R^{(k)}$ is the data number in the cluster. This process is iterated, and if the clustered results do not change, the calculation is terminated.

Based on the above theory, we calculated the values using the data obtained from the tests. All statistical processing, including cluster analysis, was performed using IBM SPSS Statistics Version 23. Given that individuals' ideas and tastes differ, the goal of this study was to determine how the participants' feelings about sporty engine sound are typically divided and to classify them effectively. Thus, K-means clustering was conducted to obtain the results. As shown in Table 4.1, for cluster count K = 2, the data of 7 jury test evaluators were assigned to Group A and those of 13 to Group B, and these were then allocated by closeness to the centroid. Table 4.2 shows the shift from the center position of the initial clusters to that of the final cluster centers after iterative calculation. Using these results, factor analysis was conducted, as well as multiple linear regression analysis for quantification. For this, we utilized only the data of the evaluators classified into each group rather than the data of all the evaluators.

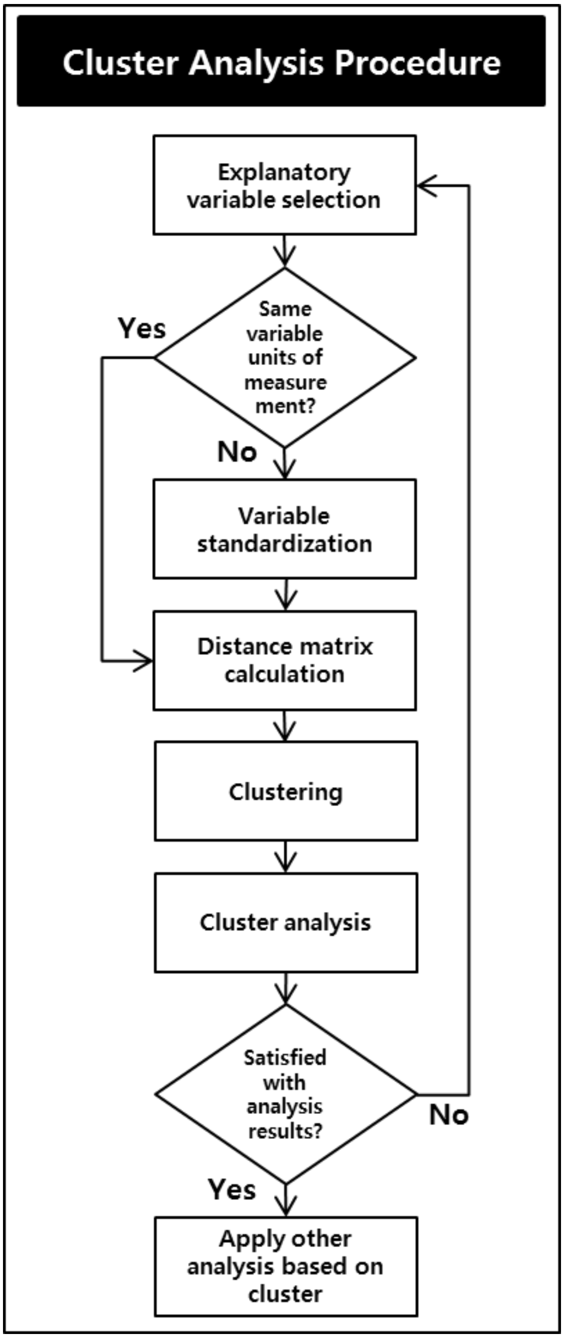


Figure 4.1 Cluster analysis procedure.

Table 4.1 Results of allocating evaluators to groups using K-means clustering algorithm and distance from final cluster center.

Jury Number	Cluster	Distance
1	A	4.006
2	B	2.456
3	B	3.387
4	A	3.390
5	B	4.380
6	A	3.791
7	B	2.208
8	A	2.611
9	A	3.592
10	B	2.535
11	B	1.592
12	B	2.361
13	B	2.506
14	B	2.718
15	B	1.888
16	A	3.422
17	B	1.506
18	B	1.271
19	B	4.179
20	A	3.277

Table 4.2 Change in distance from initial cluster centroid to that from final cluster centroid for each sample through iterative calculation.

Sample	Initial Cluster Centers		Final Cluster Centers	
	A	B	A	B
1	1.531	-0.481	-0.481	0.293
2	0.467	0.467	-0.215	0.191
3	-0.309	1.111	-0.511	0.347
4	0.112	0.754	-0.347	0.408
5	-0.249	0.569	-0.560	0.380
6	-2.569	0.000	-0.612	0.461
7	0.030	-1.339	-0.557	0.398
8	-1.780	1.310	-0.456	0.537
9	0.573	-1.938	0.394	-0.055
10	0.479	-1.464	-0.169	0.030
11	0.524	-0.079	-0.423	0.199
12	0.266	0.266	-0.358	0.333
13	-2.054	1.096	-0.704	0.490

4.2.2 Factor analysis after K-means clustering

As mentioned in Chapter 3, factor analysis is a statistical method that finds potential common factors and analyzes the correlation between the evaluation items and variables to assign meaning to the factors, thus identifying the characteristics to be known. As such, factor analysis facilitates analyzing the data evaluated using the semantic differential method. The efficiency of factor analysis was confirmed through a preliminary study [6] and Chapter 3. In the following section, results which would carry more information were sought using factor analysis after having applied K-means clustering.

Factor analysis was conducted using only the data of each group classified through cluster analysis. In addition, we performed factor extraction using principal components, determining the appropriate number of factors by checking the eigenvalues. Generally, the appropriate number of factors is determined using an eigenvalue threshold of 1 [45]. As shown in the scree plots in Fig. 4.2, there are two eigenvalues of 1 or more for each group: 4.717 and 1.669 (Group A) and 4.637 and 1.881 (Group B). This indicates that only two common factors that can be represented suffice to explain all of the data, and they have an explanatory power of 91.233% (Group A) and 93.122%

(Group B). For describing the feeling of "sportiness," the factor loading values in Table 4.3 show that the two main factors extracted can represent the several adjective pairs. In terms of meaning, Factor 1 is related to the loudness or modulation of the sound, and Factor 2 is related to the sharpness of the sound or the ratio of the tone. Thus, by finding the meaning of the target concept, the factor analysis shows that the feelings commonly felt by individuals converge into a concept, whose meaning then materializes.

To verify whether the factor analysis was appropriate and whether it was performed well, we used the Kaiser-Meyer-Olkin (KMO) test, Bartlett's test, and Cronbach's alpha coefficient. The KMO test and Bartlett's test determine the suitability of data in a factor analysis. The criteria are a KMO value of 0.5 or more and a p-value of less than 0.05 [45]. Cronbach's alpha is a measure of reliability for an evaluation item that gauges the consistency of an evaluator's responses to the question items. The criterion for this is a value of 0.7 or more [48]. Table 4.4 summarizes the results; all of the values are good and meet the significance level. Based on the validity of the factor analysis, the regression analysis was performed using the factor score results for the two groups.

Table 4.3 Component matrix showing the factor loading values for each group obtained from factor analysis. Two common factors were extracted for each group; what they represent can be seen in the meaning of the adjectives.

	Group A Factor		Group B Factor	
	1	2	1	2
Strong–Weak	**0.976**	-0.157	**0.957**	0.193
Overwhelming–Comfortable	**0.940**	-0.294	**0.940**	0.268
Dynamic–Static	**0.959**	0.185	**0.927**	0.351
Stereophonic–Simple	**0.943**	-0.012	**0.925**	0.020
Thick–Thin	**0.794**	-0.576	**0.941**	-0.239
Sharp–Soft	0.451	**0.828**	-0.189	**0.944**
Clear–Ambiguous	0.488	**0.711**	-0.449	**0.838**

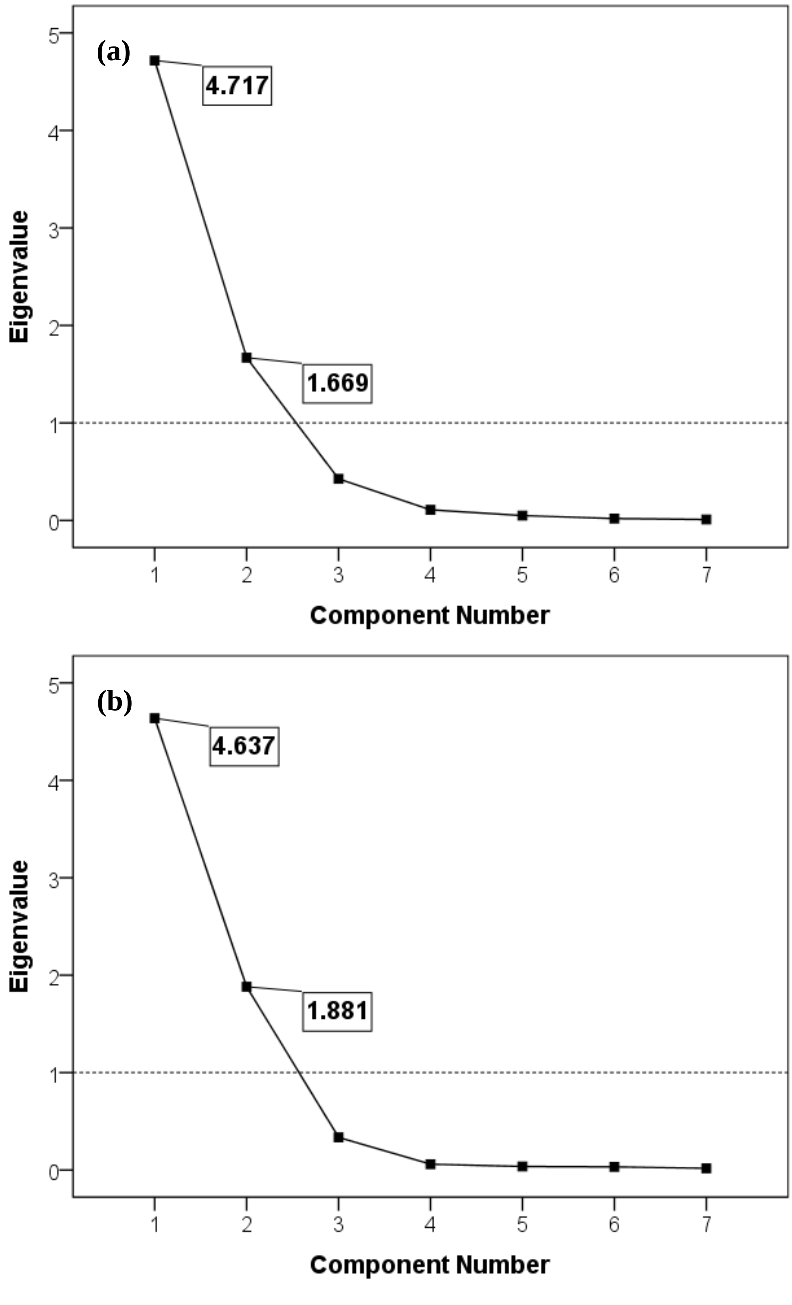


Figure 4.2 Scree plots to determine the appropriate number of factors in factor analysis. (a) Group A. (b) Group B.

Table 4.4 Cronbach's alpha, Kaiser-Meyer-Olkin (KMO) test, and Bartlett's test for validation of factor analysis.

Cluster		A	B
Cronbach's Alpha		0.913	0.818
KMO Measure of Sampling Adequacy		0.713	0.773
Bartlett's Test of Sphericity	Approx. Chi-Square	111.253	110.715
	df	21	21
	Significance	0.000	0.000

4.2.3 Multiple linear regression analysis after K-means clustering

In this section, the dependent variable is “sportiness,” and the explanatory variables correspond to the factors and parameters calculated as described in section 2.2.3. Thus, to identify the relationship between the sportiness of the vehicle engine sound and the objective parameters for each group, we first perform a first-order regression analysis between “sportiness” and the extracted factors. In the next step, the factor becomes the dependent variable, and a second-order regression analysis is conducted for the factor and psychoacoustic and acoustic parameters. Finally, the results are substituted into the first-order regression to reveal the relationship. Thus, finally, we obtain two equations because the data are divided into two groups in the cluster analysis.

First, the regression analysis was performed between the sportiness score of the jury test and the factor score obtained through factor analysis. Here, the relationship between the variables representing the differences by group is as follows.

$$Sportiness_{\mathrm{A}} = 4.418 + 0.904 \times F1_{\mathrm{A\_loud\_related}} - 0.441 \times F2_{\mathrm{A\_sharp\_related}} \tag{4.4}$$

$$Sportiness_{\mathrm{B}} = 5.249 + 0.835 \times F1_{\mathrm{B\_loud\_related}} + 0.405 \times F2_{\mathrm{B\_sharp\_related}} \tag{4.5}$$

As shown by Eqs. (4.4) and (4.5), the sportiness preferences of each group classified in the cluster analysis increased as the parameters related to the loudness of both groups increased. Moreover, for the sharpness of sound, Group A and Group B showed opposite tendencies. The standardized coefficient shows the influence of each variable on preference. The standardized coefficient is the product of the regression coefficient β_p and the ratio of the standard deviations of the independent and dependent variable data. In Group A, the standardization coefficients of Factor 1 and Factor 2 were 0.851 and −0.415, respectively, and in Group B, 0.875 and 0.425, respectively; thus, Factor 1 exhibited a greater effect on the dependent variable than Factor 2. This indicates that when people think of sportiness, they are more responsive to the parameters related to loudness.

Next, as described above, a regression analysis was performed between the factors and various sound metrics to objectively define the preference for sportiness. Because there are several types of independent variables, the stepwise regression method was used to select the variables for the multiple regression analysis. This method is a combination of forward selection and backward elimination; each time a new variable is added, the importance of each existing independent variable is checked to determine whether to keep it or eliminate it. Eqs. (4.6)-(4.9) show the results.

$$F1_{\mathrm{A\_loud\_related}} = -10.197 + 0.080 \times \mathrm{SPL_{OA}} + 2.423 \times \mathrm{Roughness} \tag{4.6}$$

$$F2_{\mathrm{A\_sharp\_related}} = -4.156 + 3.218 \times \mathrm{Sharpness} \tag{4.7}$$

$$F1_{\mathrm{B\_loud\_related}} = -14.286 + 0.206 \times \mathrm{SPL_{OA}} \tag{4.8}$$

$$F2_{\mathrm{B\_sharp\_related}} = -4.519 + 3.499 \times \mathrm{Sharpness} \tag{4.9}$$

Among the numerous candidate groups for sound metrics, we selected the variables according to their importance in causality with the dependent variable. $\mathrm{SPL_{OA}}$ represents the overall value of the A-weighted sound pressure level, and sharpness and roughness represent the psychoacoustic parameters. Eqs. (4.6)-(4.9) show that through the factor analysis of the data obtained from the participants' subjective evaluations, the abbreviated results match the objective parameters well. This indicates that it is suitable for expressing sportiness objectively and that the regression model based on this is well constructed.

Finally, by substituting the above equations into Eqs. (4.4) and (4.5), the target result can be derived from the following:

$$\begin{aligned} Sportiness_{\mathrm{A}} = -2.967 + 0.072 \times \mathrm{SPL}_{\mathrm{OA}} + 2.190 \\ \times \mathrm{Roughness} - 1.419 \times \mathrm{Sharpness} \end{aligned} \tag{4.10}$$

$$\begin{aligned} Sportiness_{\mathrm{B}} = -8.510 + 0.172 \times \mathrm{SPL}_{\mathrm{OA}} + 1.417 \\ \times \mathrm{Sharpness} \end{aligned} \tag{4.11}$$

Thus, the meaning of sportiness is interpreted differently according to the person's preference. For Group A, the greater the $\mathrm{SPL}_{\mathrm{OA}}$ and roughness and the smaller the sharpness, the higher the sportiness score. Meanwhile, for Group B, the greater the $\mathrm{SPL}_{\mathrm{OA}}$ and sharpness, the higher the sportiness score. Thus, in quantifying sportiness, cluster analysis can be used even when the population is not large enough to represent a single outcome from the overall data. In this way, the opinions of minority groups are not excluded as outliers; rather, we can find other commonalities and segment their definitions.

To determine the significance of the regression model obtained in the regression analysis, the p-value was used to determine whether the independent variable had a significant effect on the dependent variable. We also identified the adjusted coefficient of determination R^2_{adj} representing the explanatory power of the dependent variable, as well as the variation inflation factor (VIF) that examines multicollinearity, which is independent between variables. Table 4.5 summarizes all of the results. In Eqs. (4.4) and (4.5), obtained from the factor analysis results, multicollinearity does not need to be considered because it is extracted completely independently of the factors. The VIF index between independent variables is usually judged to not show multicollinearity if it is less than 10; because the range for VIF in this study is 1.000–1.782, the data are deemed suitable for regression analysis.

As a result of the multiple regression analysis, as all of the p-values are less than 0.05, all independent variables have a significant effect on the dependent variable, and for both groups, Factor 1 has a greater effect on sportiness. Among these variables, roughness showed the greatest effect (in Group A), indicating that it is the most important variable. The explanatory powers of the regression equations for Groups A and B were 87.6% and 93.5%, respectively.

Table 4.5 Results of regression equations obtained through linear regression analysis between dependent and independent variables.

Dependent variable	Independent variable	β_p	Standardized coefficient	t	p	VIF	R^2_{adj}
$Sportiness_{\text{A}}$	Constant	4.418					0.876
	$F1_{\text{A\_loud\_related}}$	0.904	0.851	8.373	0.000	1.000	
	$F2_{\text{A\_sharp\_related}}$	-0.441	-0.415	-4.084	0.002	1.000	
$F1_{\text{A\_loud\_related}}$	Constant	-10.197					0.900
	SPL_{OA}	0.080	0.357	2.930	0.015	1.782	
	Roughness	2.423	0.682	5.596	0.000	1.782	
$F2_{\text{A\_sharp\_related}}$	Constant	-4.156					0.590
	Sharpness	3.218	0.790	4.274	0.001	1.000	
$Sportiness_{\text{B}}$	Constant	5.249					0.935
	$F1_{\text{B\_loud\_related}}$	0.835	0.875	11.916	0.000	1.000	
	$F2_{\text{B\_sharp\_related}}$	0.405	0.425	5.782	0.000	1.000	
$F1_{\text{B\_loud\_related}}$	Constant	-14.286					0.824
	SPL_{OA}	0.206	0.916	7.566	0.000	1.000	
$F2_{\text{B\_sharp\_related}}$	Constant	-4.519					0.714
	Sharpness	3.499	0.859	5.568	0.000	1.000	

4.3 Validation

In addition to checking whether the derived regression equations are statistically significant, this study attempted to verify the accuracy on new samples. This can be determined by the correlation between the scores from the objective data and the scores from the jury test (Eqs. (4.10) and (4.11)). Accordingly, we produced new samples for further evaluation. A total of eight samples were produced, and an order filter was used to modulate the order components. Table 4.6 shows the calculated data. For the jury test, a total of 15 males (mean age 30.2 years) participated in the hearing evaluation, and the evaluation was conducted in the same environment as described in Section 2.3.2. As before, the results of inconsistent evaluators (3 participants) were excluded, resulting in the data of 12 participants. The jury test used a seven-point rating scale. The evaluator listened to the sound and directly selected the score and rank.

To identify the groups to which the new evaluators belonged, we compared the correlations of the scores of the individually felt sportiness and the scores from Eqs. (4.10) and (4.11); the higher coefficients were classified, and those without a high correlation coefficient in either group were excluded (two participants). Finally, five participants were assigned to

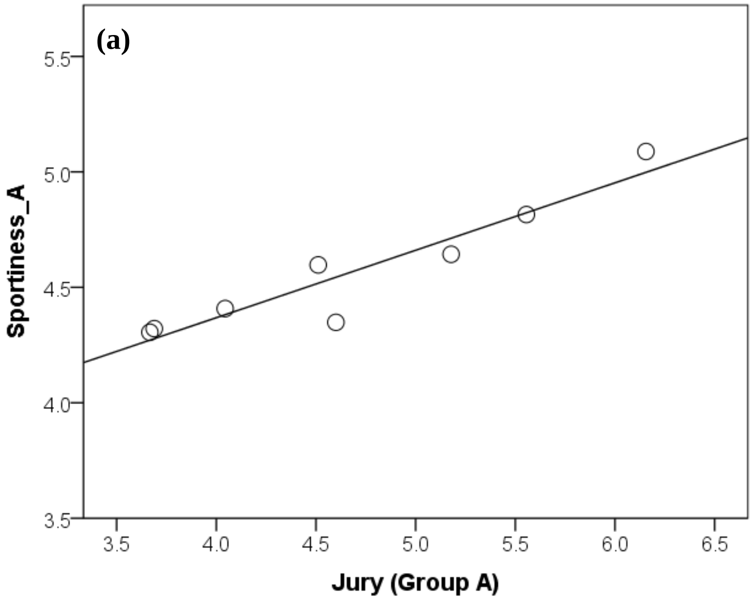
Group A and five to Group B. We then conducted a correlation analysis to investigate how well the sportiness scores of each group represent the developed regression scores. The results are shown in Table 4.7, and graphs are shown in Fig. 4.3. As shown in the table, the correlation coefficients R for Groups A and B were 0.942 and 0.930, indicating highly accurate results. This can be further segmented by grouping the sporty sound of the vehicle engine, which feels different for each individual participant in this study, through cluster analysis. The objective sound quality indices thus obtained can meaningfully represent the thoughts of the new evaluators for the new samples as well.

Table 4.6 Calculations of single values of acoustic and psychoacoustic parameters for new samples.

Sample	SPL_{OA} (dBA)	Loudness (sone)	Sharpness (acum)	Roughness (asper)	Tonality (tu)
1	70.10	23.80	1.06	1.71	0.390
2	71.90	25.50	1.05	1.87	0.392
3	74.70	29.90	1.02	1.68	0.456
4	75.30	30.20	1.03	1.87	0.459
5	71.10	25.40	1.06	1.67	0.411
6	70.07	24.20	1.06	1.73	0.403
7	71.00	24.50	1.05	1.80	0.393
8	71.50	24.50	1.05	1.67	0.417

Table 4.7 Results of jury test and regression sportiness scores and correlation coefficients for each group.

Sample	Jury Group A	$Sportiness_{\mathrm{A}}$	Jury Group B	$Sportiness_{\mathrm{B}}$
1	3.689	4.321	3.400	5.049
2	5.556	4.815	4.556	5.345
3	5.178	4.643	5.156	5.784
4	6.156	5.088	5.778	5.901
5	3.667	4.305	3.867	5.221
6	4.044	4.408	3.622	5.152
7	4.511	4.597	4.222	5.190
8	4.600	4.348	4.711	5.276
Correlation Coefficient R		**0.942**		**0.930**



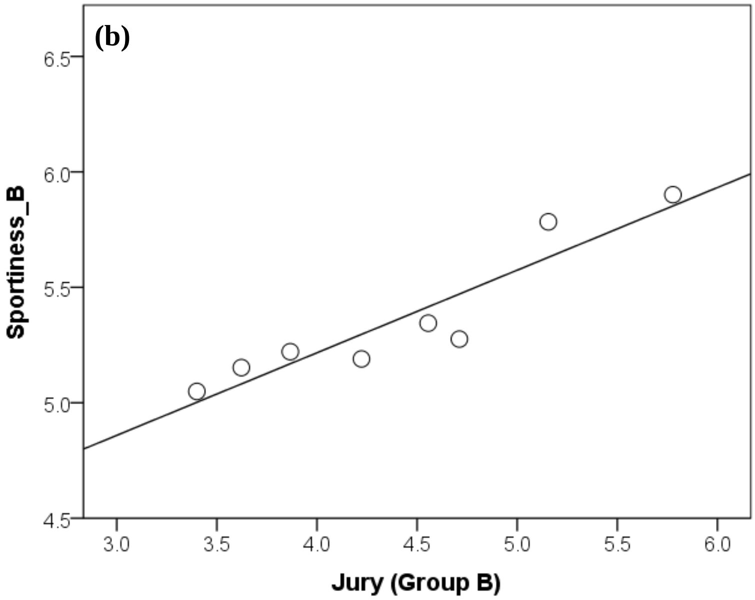


Figure 4.3 Correlation between the jury test scores and the sound quality evaluation scores for each group, to validate the regression equations developed. (a) Group A: R = 0.942. (b) Group B: R = 0.930.

4.4 Summary

In Chapter 4, a sound quality evaluation index that can further improve the accuracy of the sound quality index developed in Chapter 3 for representing sportiness and can represent the meaning of "sportiness" according to individuals in a more concrete manner, was developed. Accordingly, based on the results of the jury test, statistical analysis is required to convert the data obtained from subjective evaluations, such as jury testing, into quantitatively formulated data. The process to accomplish this consisted of cluster analysis, factor analysis, and linear regression analysis. For cluster analysis, we used the K-means clustering algorithm, which distributes the data reflecting differences in the evaluators' preferences. Based on the distances in the distribution, the distances of similar responses can be quickly tied together, thus forming two subgroups of evaluators. The data from the two groups were then divided into two populations and used for the factor analysis. Two common factors were extracted from each group: Factor 1 is related to the loudness of the sound, and Factor 2 is related to the sharpness of the sound. The explanatory power, which indicates how well the two common factors describe all of the data, is 91.233% (Group A) and 93.122% (Group B). The factor scores obtained through the factor analysis were subjected to a regression analysis with the sportiness score responses from the jury test, and the results were analyzed mathematically (first-order regression analysis). Because factor analysis was performed, an additional regression analysis between the factors and the calculated sound metrics was necessary (second-order regression analysis). Thus, we were able to finally determine the relationship between sportiness and sound metrics by substituting the results into the first-order regression. Eqs. (4.10) and (4.11) show the final results. In both groups, the influence of Factor 1, which is related to the loudness of the sound, was greatest. In Group A, as $\mathrm{SPL_{OA}}$ and roughness increased and sharpness decreased, the sportiness score rose; of these, roughness had the greatest effect. In Group B, both $\mathrm{SPL_{OA}}$ and sharpness showed a positive correlation. Furthermore, for the derived regression equations for $Sportiness_{\mathrm{A}}$ and $Sportiness_{\mathrm{B}}$, the regression model was found to be suitable based on the high coefficients of determination 0.876 and 0.935, appropriate p-values, and VIF values.

Verification steps were taken to ensure that the developed indices show reliable results when used with new samples and new evaluators. The evaluators were allocated to either Group A or Group B depending on whether their individual responses showed a higher correlation with Eq. (4.10) or Eq. (4.11). The correlation coefficients R between the average score of each allocated group and the sportiness score of the developed index were checked to verify the reliability of the equations. The correlation coefficients R of the results were 0.942 (Group A) and 0.930 (Group B), indicating a very high correlation. Consequently, the conformity of research methods and results could be verified using K-means clustering, which can be used to develop the sound quality evaluation index.

CHAPTER 5

CONCLUSIONS

This study sought to determine what it means for a sound to be “sporty” and to objectively define this abstract concept in terms of engine sound, which is the main source of noise generated inside a vehicle. For this purpose, it was essential to measure the engine sound of an actual vehicle, play back the sound to people for them to evaluate, and determine the relationship between the two through statistical processing. In this process, the evaluation items were composed by finding adjective pairs that can represent the sportiness with which people think of using the semantic differential method. Subsequently, the validity and necessity of factor analysis were improved by collecting items with a high correlation for investigating the characteristics of sportiness through factor analysis and expressing them as representative factors, thereby giving them meaning. In addition, taking the different expressions of “sportiness” based on the preferences or tastes of the evaluators, we used cluster analysis to classify the groups with commonalities and developed sound quality evaluation indices for each group. Thus, we sought to further specify the meaning and broaden the range for expressing sportiness.

Accordingly, based on a typical sound quality study, K-means cluster analysis and factor analysis were performed, and the results obtained not only showed high explanatory power but also showed a very high correlation when applied to new samples. This indicates that the developed sound quality evaluation indices reflect the tastes of evaluators regarding the sportiness of engine sound and can serve as useful indices that objectively quantify this subjective concept based on statistical significance and can also provide accurate results for new evaluators.

However, as this study did not have a correct answer for the number of clusters *K*, a disadvantage of K-means clustering, a method is necessary for selecting the optimal number of clusters *K*. Furthermore, no guidelines have been established for identifying new customer tendencies and classifying them into appropriate clusters. Also, a few limitations were observed in the jury test. Although the reliability of the developed evaluation index through the responses of new evaluators during the verification has been achieved, it is necessary to organize and run the evaluations on more populations because the increasing number of test subjects can produce more accurate results leading to a more concrete description of sportiness. In addition, since the effect of characteristics such as age or gender were not considered when surveying preferences, the study of the correlation between these variables and sportiness of a large population size could prove to present some interesting insight that might even become the subject of a separate study. Therefore, further research is required to address these issues, which may lead to more nuanced results. Nevertheless, the method proposed in this study can be used to predict sportiness scores while considering differences in individual taste without the need for a time-consuming jury test during the vehicle development stage. The evaluation indices derived in this study can serve as the basis for judgment and will facilitate the determination of directions for vehicle development. The scope of research can be further broadened by considering the regional and cultural characteristics of the customer base, thereby assisting car manufacturers or developers in devising customized sales strategies that target specific customers.

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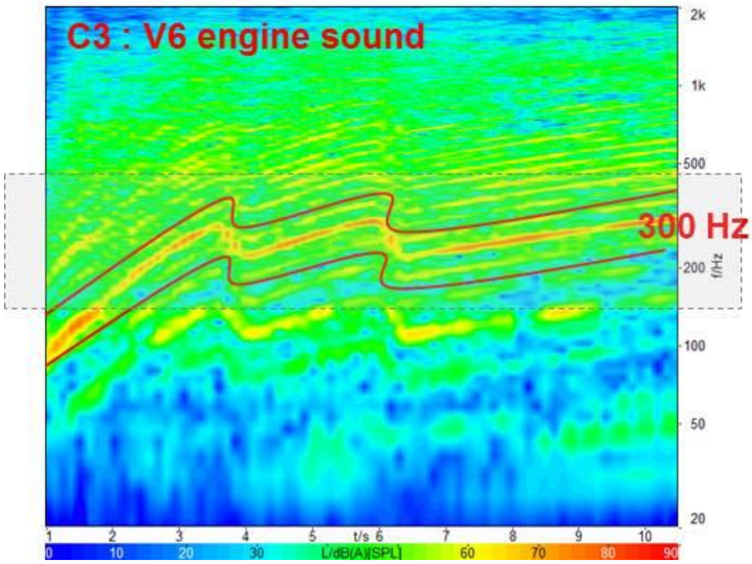
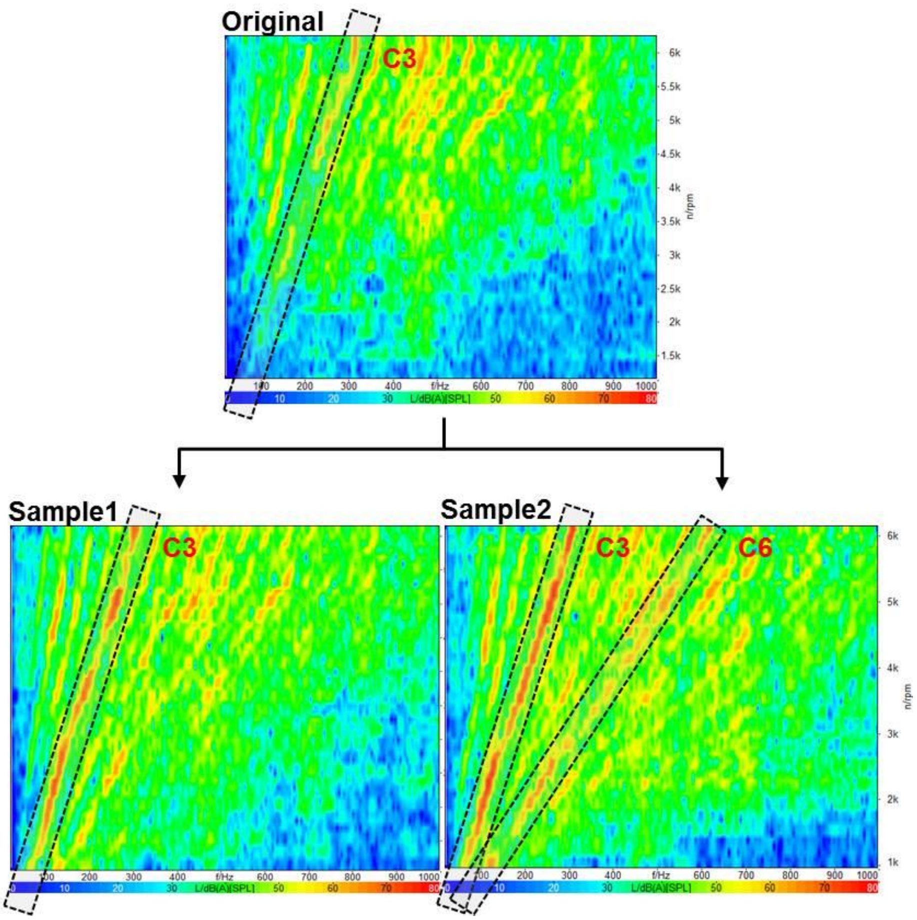
APPENDIX

VALIDATION FOR 6-CYLINDER ENGINE SOUND

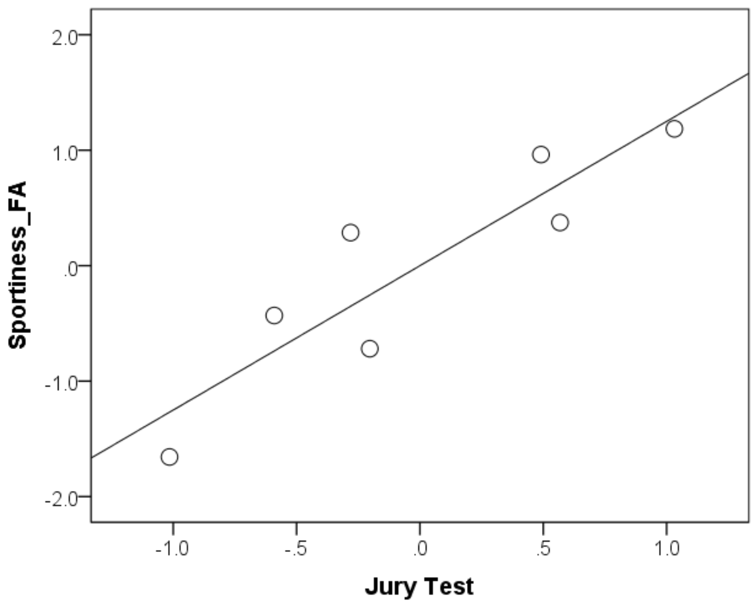
Further verification was carried out to validate the applicability of the Sportiness index, as developed in Chapter 3 using a 4-cylinder vehicle, on any other target vehicle. The target vehicle was equipped with a V6 engine the experimental conditions and procedures were the same as those described in Chapter 2. As can be seen from the color map below, for the V6



engine, the third order component is prominent as opposed to the 4-cylinder engine. Furthermore, the frequency range of the third order component fluctuates between 60-350 Hz depending on the operating conditions. The samples used for the subject evaluation were recorded by replacing the muffler of the original vehicle, and the difference in engine sound characteristic can be observed by comparing the order components as seen in the figure below. Muffler structure differences have various effects on the engine sound, they can amplify third order components leading to an accentuation of booming sounds. Or they can also cause in-phase vibrations



with the parts around the engine pistons leading to a reinforcement of the harmonic components. A total of 7 samples were recorded including the original vehicle's engine sound and the engine sound of the same vehicle with 6 different mufflers from 4 different manufacturers. The rating method was applied, using the recorded samples, and the jury test was conducted, requiring 12 evaluators, 10 males and 2 females with an average age of 28.2, to rank the 7 samples in order of sportiness. The results obtained are shown in the graph and table below, and are represented using standardized scores and correlation between the jury test and the index. A correlation coefficient R of 0.903 means that the index developed is highly reliable and can be used to represent sportiness preferences despite target vehicle changes. Ultimately, clustering becomes more effective with a larger population that is more diverse and using a bigger variety of test samples. By further improving the limits discussed in this study, a more powerful model can be developed.



	Jury Test	*Sportiness*$_{FA}$
Sample 1	-0.203	-0.719
Sample 2	0.568	0.373
Sample 3	-0.590	-0.432
Sample 4	1.032	1.186
Sample 5	-1.015	-1.657
Sample 6	0.490	0.962
Sample 7	-0.281	0.286
Correlation coefficient *R*		**0.903**

국 문 초 록

현재 차량 개발 기술이 발전함에 따라 차량의 NVH 성능이 많이 개선되었고, 이로 인해 소음 저감의 측면보다 듣기 좋은 소리와 같은 음질 측면에서의 소비자의 수요가 계속해서 증가하고 있다. 스포티한 엔진음이 그 범주에 속하고, 이는 사람마다 떠올리는 이미지가 다르고 소리에 대한 취향의 차이가 발생하는 주관적인 개념이다. 따라서 본 연구는 음질 연구를 통해서 그러한 개념의 객관적인 의미를 찾아 정량적으로 표현하고, 취향의 차이가 발생하는 것을 수용할 수 있는 방법을 찾기 위해 진행되었다. 본 논문에서 중점적으로 다루는 내용은 크게 두 가지이다. 첫 번째는, 스포티함의 음질 지수를 개발함에 있어 요인 분석을 활용함으로써 요인 분석의 효율성을 확인하고자 한 것이고, 두 번째는, K-평균 군집 분석을 추가하여 음질 지수의 정확도를 더 향상시키고 스포티함의 의미를 더욱 구체화하고자 한 것이다.

따라서, 본 논문의 2장과 3장에서는, 양산되고 있는 차량 4대를 wide open throttle 조건에서 엔진음을 녹음하였고, 녹음된 소리로부터 parametric band-pass filter를 사용해 신호를 변조하여 13개의 샘플을 제작하였다. 제작된 샘플의 음향심리학적 매개변수들을 계산하였고, 청음 평가를 통해서 스포티함에 대한 선호도를

파악하였다. 청음 평가는 23명의 평가자가 참여하였고, 의미미분법을 사용해 스포티함의 선호도와 스포티함을 잘 설명할 수 있는 형용사들을 찾아냈다. 그 결과를 요인 분석에 적용해 사람들이 공통적으로 느끼는 스포티함의 특성을 두 요인으로 표현하였고, 평가 결과간 다중 선형 회귀 분석을 이용해 관련된 음질 인자로 표현할 수 있는 스포티함 정량화 지수를 개발하였다. 개발된 지수는 새로운 샘플군을 통해 상관계수를 확인하여 그 유효성이 확인되었다. 또한, 요인 분석 사용 유무에 따른 회귀식의 결과를 비교함으로써 요인 분석의 필요성에 대해서도 언급하였다. 4장에서는, 스포티함에 대한 평가자들의 성향 차이가 발생하는 것을 토대로 K-평균 군집 분석을 활용해 각 집단에 맞는 회귀식을 개발하기 위해 요인 분석과 다중선형회귀 분석을 재수행하였다. 개발된 지수의 신뢰성을 역시 확보하기 위해 새로운 평가자들로 재검사하였고 높은 상관계수를 토대로 그 신뢰성을 입증하였다.

결과적으로, 본 연구를 통해 개발된 음질 평가 지수는 스포티함을 객관적으로 정의함에 있어 또 다른 공통성을 나타내는 집단의 의견까지도 반영할 수 있고 정확도 높은 결과를 산출해주는 유용한 지수이다.

주요어 : 음질 평가 지수, 차량 엔진음, 스포티함, 의미미분법, K-평균 군집 분석, 요인 분석, 다중 선형 회귀

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