Chapter 16
Kansei Quality in Product Design

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Abstract Kansei quality is a product quality that evokes the customer's specific impressions, feelings, and emotions – such as comfort, luxury, delight, *etc.* It is important to consider kansei quality especially when designing mature consumer products. One of the most important issues in the design of kansei quality is to construct the evaluation criteria of the target kansei qualities. Without such criteria, the designer has to rely only on his/her subjective criteria for designing and evaluating kansei quality. We often express such a quality using adjectives that are subjective and often ambiguous. However, the meaning and sensitivity of adjectives may differ from person to person. Moreover, we possess latent evaluation criteria that are often evoked by new experiences, such as seeing a new product that provides a new kansei quality. In this chapter, the author presents a method to construct evaluation criteria for kansei quality, taking into consideration the diverse and latent kansei of customers. As a case study, the author applies the method to the design of a product's sound quality.

16.1 What Is Kansei Quality?

Customers' needs towards consumer products become diverse in a mature market where many products have similar functionalities and performance. With such diversification, the customer has come to focus more on the emotional and sensuous quality of a product.

A *kansei quality* is a product's quality that evokes the customer's specific impressions, feelings, or emotions towards a product (*e.g.*, comfort, luxury, delight) [1]. *Kansei* is originally a Japanese word that refers to the sensitivity of a human

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sensory organ at which sensations or perceptions take place in response to stimuli (*e. g.*, a product) from the external world. Kansei includes evoked senses, feelings, emotions, and impressions. The word kansei has begun to be used internationally because there is no suitable translation in English.

According to the psychologist A. Maslow, human needs shift from common physiological needs to personal psychological needs [2]. This view suggests that sensuous needs are likely to increase further in the future. To respond to such continuously diversifying sensuous needs, it has become important to determine the customer's effective needs and to design according to those needs. It is, however, difficult to grasp such sensuous needs as compared to other needs because sensuous qualities are subjective, not easy to externalize, and often latent.

The most important issue in the design of kansei quality is extracting quantitative criteria for evaluating such a quality. Without such quantitative criteria, the designer cannot set a clear goal for design because he/she is not sure what kind of evaluation criteria the customers have, or how to design a product to increase a target kansei quality. The designer has to rely on his/her assumptions based on sensitivity and tacit knowledge. If there is a gap between the designer and customers in terms of their sensitivities, the designer may misinterpret how a customer will evaluate his/her design.

16.2 Approaches Towards Kansei Quality in Product Design

Kansei qualities are often represented by subjective words, such as adjectives. Several methods employing sensory tests have been used to evaluate a product's kansei quality represented using words. The *semantic differential method* (SD method) [3], which is widely used, uses pairs of opposite words to evaluate the kansei quality of evaluation samples. The subjects score the degree of their impression towards product samples according to five to seven ranks between the word pairs. To measure the emotional score more precisely, pair-wise comparison [4] is often used. Two samples are randomly selected and the subject scores one sample by comparing it with the other sample in terms of a specific kansei quality. Although this method enables the precise measurement of kansei qualities, the number of trials increases exponentially with the number of samples because of the number of possible combinations.

Most approaches to sensitivity quantification aim to make generalizations of sensitivity by averaging the subjects' evaluations. A mapping between the averaged kansei score and measurable design attributes is created. Several mapping methods have been developed and used, such as multi regression analysis, fuzzy reasoning, and neural networks [5]. *Reduct* in rough set theory [6, 7] has recently been noticed as a method of knowledge acquisition that is useful for design [8].

The constructed mapping serves as a metric of general kansei qualities. However, by nature, human sensitivity differs from person to person. Highly subjective perceptions that are directly related to product value, such as pleasantness and preference, are particularly highly individualistic. Few researches deal with the individuality of sensitivity. Nakamori applies fuzzy set theory to represent sensitivity individuality [9]. In his method, the degree of individuality is represented by the fuzziness of a fuzzy set whose center is an average value. This approach regards individuality as errors from the average value. Causes of personal differences cannot be explained using this method.

Yanagisawa and Fukuda found semantic differences in emotional words between designer and customer using the SD method and *principal component analysis* (PCA) [10]. An emotional word contains multiple scales of semantics that vary from person to person. There is little point in averaging between scales that have different meanings. An averaged kansei quality cannot be used to represent diverse sensitivities.

There is another approach in which the individual customer is assisted to evolve design samples to meet his/her psychological satisfaction through the interaction of analysis and synthesis. A customer's evaluations of provided design samples generate new design samples, allowing recursive refinement. However, from the standpoint of the customer, it is desirable to keep questionnaires to a minimum – *interactive evolutional computation* (IEC) [11] is one solution to this problem. Human evaluation is regarded as the fitting function of an evolutional computation (EC) such as a genetic algorithm (GA), where the design parameters are coded as chromosomes. Users evaluate the design samples generated by the EC, and then the EC generates the next generation's design samples. Users only need to evaluate the design samples until they arrive at a satisfying result. There are some applications of IEC for design support systems [12, 13]. In this approach, analysis and synthesis interact with each other for short periods. Because human preferences and sensitivities change as they are influenced by the design samples, this scheme is suitable for supporting personal design.

16.3 Towards Diverse and Latent Kansei

In this section, we focus on two characteristics of human sensitivity that are important to consider when designing kansei quality. The first characteristic is the *diversity* of human sensitivity. Human sensitivity towards kansei quality is different from person to person. In other words, individual differences of sensitivity exist. Although we share common senses for some basic kansei qualities, they do not always cover all of the kansei qualities that relate to a product's value.

When we say "individual differences" of sensitivity, we must be careful to note that there are two kinds of individual differences: *variation* and *diversification*. *Variation* is an individual difference that can be measured by a unique scale (see Figure 16.1 (a)). For example, the sense of heaviness in a sound may be slightly different from person to person but the meaning of heaviness should be universal. We can apply statistical operations such as averaging to such data. We can use the standard deviation as an indicator of the individual difference. Most conventional approaches to individual differences of sensitivity deal with this type of difference. In other words, individuality is regarded as an error from the average value.

On the other hand, *diversification* represents individual differences of the scales themselves (see Figure 16.1 (b)). For example, the sense of beauty may have multiple different scales depending on personal viewpoints. We cannot use statistical operations between different scales, such as averaging between length and weight. Higher and more complex kansei qualities tend to have this diversification. These kansei qualities tend to directly relate to product value.

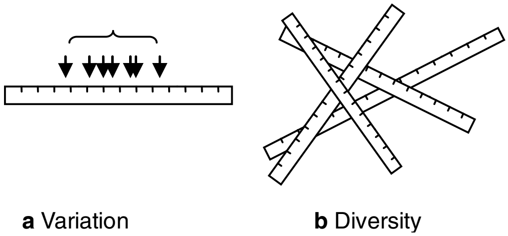

Figure 16.1 Difference between (a) variation and (b) diversity

The second characteristic of human sensitivity is the *latent* sensitivities that we potentially possess – although we are not consciously aware of them – which are evoked by new experiences. Most conventional approaches construct the evaluation criteria for kansei qualities using existing products on the market as evaluation samples, and their sensory evaluations are scored by human subjects. The constructed evaluation criteria are then used to evaluate new designs. However, existing products are not exhaustive enough in the design space to construct general evaluation criteria that can be used for future design. People may evoke different latent sensitivities towards an unknown design sample. In other words, the constructed evaluation criteria may not be applicable for evaluating and designing new designs.

16.4 A Method for Extraction of Diverse and Latent Evaluation Criteria of Kansei Quality

This section presents a new method on how to extract and formalize *diverse* and *latent* evaluation criteria toward kansei quality [14, 15]. The method consists of two sensory tests. The first sensory test uses evaluation samples of existing products; the second uses both composite samples and existing samples in order to extract latent evaluation criteria. Composite samples are created in the design feature areas untouched by existing products by modifying the features toward those directions that increase the target kansei quality based on multiple criteria obtained from an analysis of the results of the first sensory test. The method used is as follows:

1. Design samples were prepared from existing products. Using the samples, we conducted a sensory test based on the SD method. In the test, multiple subjects gave their impressions of the samples using pairs of opposing adjectives, called SD scales.
2. Next, we extracted the design feature values from each sample.
3. From the results of the first sensory test, we analyzed the multiplicity of each SD scale, which are different from person to person, and extracted patterns of subjective scales considering the diversity of personal sensitivities. The patterns were extracted using cluster analysis, based on the correlation coefficients between subjects for each SD scale that represent similarities of sensitivity. We formulated each extracted scale using the design features and interpreted the semantics of each subjective scale. (Details of this process are given in Section 16.4.1.)
4. Based on the formulated scales, we set feature values that are used to synthesize composite design samples. We selected an SD scale as the target kansei quality and set feature values so that they are dispersed on the scale. To extract evaluation criteria that can be used for future design, the design feature values are required to cover areas of the feature space untouched by existing products. We synthesized composite design samples to fit the set feature values by modifying the original samples of existing products.
5. A second sensory test was conducted using both the created samples and existing ones in the same manner as the first sensory test. For the SD scales, we added new SD scales or deleted old ones from the first sensory test based on their contributions.
6. We extracted and formulated multiple scales from the result.
7. To check the repeatability of the scale, the results of the first and second sensory tests were compared in terms of the SD scales commonly used in both experiments. We then analyzed the changes in kansei quality due to the addition of the new composite design samples. Finally, we extracted potential factors of the kansei evaluation criteria for designing new samples and applied factor analysis using the multiple scales obtained from the results of the second sensory test.

16.4.1 Extraction of Multiple Kansei Scales Considering Diverse Kansei Qualities

As discussed in Section 16.3, we assume that the semantics and sensitivities for SD scales (*i. e.*, pairs of adjectives), which are used as evaluation scales in the SD method-based sensory test, are diverse. In other words, subjects have *different potential scales* for each SD scale. We extracted patterns of potential scales for each adjective based on the similarity of scores obtained from the first sensory test. Figure 16.2 shows how to extract them. We used correlation coefficients between scores given by different subjects as an indicator of their similarity. It is assumed that two subjects have similar psychological scales if their respective scores for the samples are similar. To break down a scale, we apply *cluster analysis* using the correlation coefficient-based distance.

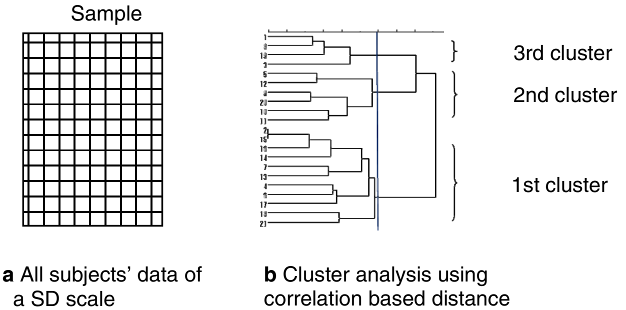

Figure 16.2 How to extract patters of personal evaluation criteria from an SD scale: (a) all subjects' data from an SD scale, and (b) cluster analysis using a correlation-based distance

First, select N_p products S_i ($i = 1, 2, \ldots, N_p$) as evaluation samples of the sensory test. N_s subjects T_j ($j = 1, 2, \ldots, N_s$) evaluate their impressions of the samples S_i using the SD method with N_w pairs of adjectives (SD scales) I_k ($k = 1, 2, \ldots, N_w$). Let $\boldsymbol{E}_{jk} = \langle e_{ijk} \rangle$ be a vector of scores given by the jth subject for all evaluation samples in terms of I_k. If the pth subject has a similar sensitivity to the qth subject in the SD scale I_k, the correlation coefficient of E_{pk} and E_{qk} should be close to 1.0. If the pth subject has the opposite sensitivity to the qth subject for I_k, the correlation coefficient should be close to –1.0. We define the distance between the pth and qth subjects in terms of the sensitivity of an SD word I_k as follows:

$$d_{kpq} = 1 - r(\boldsymbol{E}_{pk}, \boldsymbol{E}_{qk}) \quad (p \neq q), \tag{16.1}$$

where d_{kpq} is the distance and $r(\boldsymbol{a}, \boldsymbol{b})$ denotes the correlation coefficient between vectors $\boldsymbol{a}$ and $\boldsymbol{b}$.

For each SD scale, we next classify all subjects into clusters using the distance and cluster analysis; members of each cluster have similar sensitivities for that SD scale. The obtained clusters reflect a division (*i. e.*, breakdown) of the SD scale, and represent the multiple viewpoints or sensitivities of that SD scale. We derive the threshold value of the distance for cluster formation, where members of each cluster are not statistically different from each other, in terms of the sensitivity of the SD scale with significance level α.

Kansei qualities comprise a hierarchical structure as shown in Figure 16.3 [16]. The lower level of the hierarchy more directly reflects human perceptions of external stimuli. The higher level consists of more subjective kansei, such as subjective impressions (*e. g.*, beauty) and preferences. It is assumed that individuality increases as one goes higher up the hierarchical level, as shown in Figure 16.3.

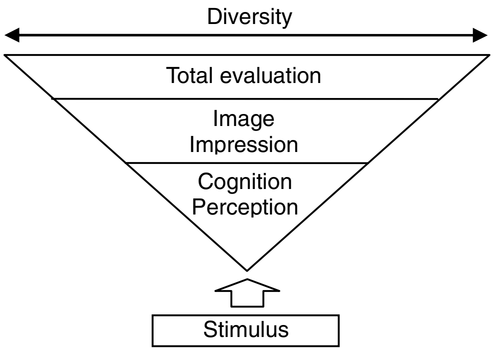

Figure 16.3 Hierarchy and diversity of emotional response

If a SD scale cannot be broken down into smaller groups by this process, which means that all subjects give statistically similar values for all evaluation samples, then that kansei is considered to be low in the kansei hierarchy. If a kansei scale can be broken down into many clusters and each cluster consists of a small number of subjects, that kansei is high in the hierarchy. We use the relative proportion of subjects that belong to a divided (*i. e.*, broken down) kansei cluster as an indicator of its *commonality*. This commonality can be used to decide the hierarchical order of each kansei word.

We define the commonality of an emotional word for each cluster as follows:

$$\mathrm{Com}_l = \#T_\mathrm{c} \,/\, \#T \times 100, \tag{16.2}$$

where $\#T$ denotes the number of subjects and $\#T_\mathrm{c}$ denotes the number of subjects included in the lth cluster C_l. The commonality is equal to 100 if all subjects have a similar (*i. e.*, statistically the same) SD scale sensitivity.

We use the average value of each cluster as a central value of the cluster. The central value of the lth cluster for the ith SD scale and kth evaluation sample is calculated as follows:

$$y = \textstyle\sum_{j \in Cl} e_{ijk} \,/\, \#T_\mathrm{c}. \tag{16.3}$$

To interpret the semantics for each cluster scale, we use correlation coefficients with the cluster scale value of other words whose commonality is higher (*i. e.*, low-level kansei quality).

16.4.2 Strategies of Setting Design Feature Values

There are two strategies for creating composite design samples, as follows: (1) cover areas of the design feature space *untouched by existing product*, and (2) disperse features on a target kansei quality considering its *diversity*. These are described in this section.

1. Finding a Design Feature Area Unexplored by Existing Products

The first strategy is to create design samples in a feature area where no existing sample appears. If the number of features is two, we can visualize the mapping of existing products to find such an area. However, if the number of dimensions of features is more than three, it is difficult to find such areas visually. To reduce the number of dimensions, we apply *principal component analysis* (PCA). PCA reduces a multidimensional space to a lower-dimensional space (2D or 3D) while retaining as much information as possible.

We extract N_f design features $P = <p_1, p_2, \ldots, p_{Nf}>$ for the evaluation samples of the sensory test. The ith principal component F_i is obtained as follows:

$$F_i = W_i'P\,, \tag{16.4}$$

where $W_i = < w_1, w_2, \ldots, w_{Np}>$ is a principal component loading. The obtained principal components are orthogonal to each other. The variance of a principal component denotes the degree to which the principal component explains the original data P. We use the two top principal components in terms of their variances to visualize the mapping of the evaluation samples. The 2D scatter graph using the selected components allows us to visually find areas unexplored by existing designs in the feature space.

2. Setting Feature Values Dispersed on the Target Kansei Quality

We set a *target kansei quality* that the designer aims to increase for future design. We create composite samples by dispersing this quality in unexplored feature areas. By analyzing the relation between such samples and their emotional responses, we can extract latent factors for such a quality.

To set such design features, we formalize a target kansei quality using the results of the first sensory test. Assume we obtain N_c clusters from the target kansei quality. We can apply *multiple regression analysis* (MRA) to formalize the target kansei quality for each cluster, using extracted design features as explanatory variables. The central value of the lth cluster $Y_l = < y_{l1}, y_{l2}, \ldots, y_{lNs}>$ is estimated as follows:

$$Y_l = A_l'F + \beta\,, \tag{16.5}$$

where $A_l = <a_{l1}, a_{l2}>$ denotes the weight vector, F is the principal component vector, and β is the error vector. A_l represents a direction in feature space for creating design samples. This direction has the potential that composite samples will be dispersed in terms of the target kansei quality.

16.5 Case Study: Product Sound Quality

The sound made by a product is an important factor that affects the product's kansei quality. For quite a long time, sound engineering dealt mainly with the reduction of the overall sound pressure level (SPL) emitted by a product. Within the last decade, however, the focus has started to switch more towards aspects related to the sound quality. The biggest change is that the design goal switched from objective values, such as "decibel" levels that can be physically measured, to subjective ones, such as kansei qualities. To design for kansei qualities of product sound, it is necessary to develop metrics to quantitatively evaluate such subjective qualities. Zwicker *et al.* [17] developed sound quality metrics (SQM) as an evaluation metric of the product sound quality. SQM provides values for simple perceptions of sound, such as loudness and sharpness. However, the kansei qualities of a product's sound include more complex affective perceptions, such as pleasant, annoying, luxurious, *etc.* To deal with such complex sensitivities in sound design, most conventional approaches conduct sensory tests using affect-laden words to score target kansei qualities. Statistical methods are used to compose a map between SQM and complex kansei qualities [18]. Several applications have been studied based on this approach [19–22]. Most research so far, however, has not considered the diversity and potentiality of human sensitivity.

16.5.1 Sound Quality Metric as Design Parameters

As measurable design parameters of product sounds, we use four basic SQM [17]: loudness, sharpness, roughness, and fluctuation strength. These are widely used and well defined. Recent studies have demonstrated that these metrics are independent of the meaning of a sound [21, 22]. We extracted these four SQM from the stationary sounds of ten products.

Loudness

Loudness is a perceptual measure of the effect of the energy content of sound in the ear. It is related to the decibel level and also depends on the frequency content of a sound. For example, a very low-frequency sound such as a 20 Hz tone at 40 dB would be perceived to be quieter than a 1 kHz tone at 40 dB. The loudness level of a sound is defined as the sound pressure level of a 1 kHz tone in a plane wave and frontal incident that is as loud as the sound; its unit is the "phon". ISO 226 constructs equal loudness contours using data from 12 references [23].

Third-octave bands can be used as an approximation to critical bandwidths, which is a measure of the frequency resolution of the ear [24]. A specific loudness can be calculated from the decibel level for each third-octave band. The value of loudness (N) is calculated as the integral of the value of the specific loudness (N'). The unit of loudness is the "sone". One sone equals 40 phons, which is the loudness of a 1 kHz tone at 40 dB in a plane wave.

Sharpness

Sharpness is a measure of the high-frequency content of a sound; the greater the proportion of high frequencies, the "sharper" the sound. Using Zwicker and Fastl's approach [17], sharpness is calculated as the weighted first moment of the specific loudness. The unit of sharpness is the "acum".

Roughness
People perceive a rapid amplitude modulation around 70 Hz of a sound as "rough". The unit of roughness is the "asper". One asper is defined as the roughness produced by a 1000 Hz tone of 60 dB, which is 100% amplitude modulated at 70 Hz.

Fluctuation strength
Fluctuation strength is similar in principle to roughness except it quantifies subjective perception of slower (up to 20 Hz) amplitude modulation of a sound. Maximal values are found to occur at a modulation frequency of 4 Hz. The unit of fluctuation strength is the "vacil". One vacil is defined as the fluctuation strength produced by a 1000 Hz tone of 60 dB, which is 100% amplitude modulated at 4 Hz.

16.5.2 Sensory Test Using Existing Samples (First Experiment)

We first carried out an impression evaluation experiment based on the SD method with 21 subjects. We recorded the stationary sounds from ten selected products of different makers in an anechoic chamber and used them as evaluation samples.

Table 16.1 SD words used with SD method-based sensory test

No.	Pair of SD words
1	hard–soft
2	dull–clear
3	silent–noisy
4	square–round
5	opaque–limpid
6	weak–strong
7	discomposed–composed
8	ugly–beautiful
9	static–dynamic
10	cheerful–gloomy
11	poor–rich
12	small–big
13	high–low
14	dislike–like
15	untypical–typical (sounds like the machine)
16	unentertaining–entertaining
17	cheap–expensive
18	effective–not effective (How good a job the machine is doing)
19	elegant–inelegant
20	agreeable–annoying
21	western–Japanese
22	unpleasant–pleasant

We selected 22 pairs of adjectives related to the target product sounds, as shown in Table 16.1. These words contain different levels of the kansei hierarchy. For example, “loud–silent” is a perceptional level kansei (low level) and “like–dislike” is a preference level kansei (high level).

We divided the subjects into four groups of five people each. The five subjects sat in front of a speaker. Each sound was played for 5 s and the subjects gave their impressions of the sounds by filling out a questionnaire consisting of word pairs. Two trials of the same experiment were conducted in order to test the reliability of the data. To avoid the influence of the learning curve, the subjects practiced responding before conducting the experiment.

16.5.3 Extracting Patterns of Personal Kansei Scales

We divided each SD scale using cluster analysis with the correlation-based distance discussed in Section 16.4.1.

Figure 16.4 shows examples of the clusters demonstrated in 2D space using *multi-dimensional scaling* (MDS) [25]. MDS is often used to compose a 2D space using only distances among samples. Each point represents a subject. The coordinate system does not have any meaning but the distances between points correspond to the correlation-based distance.

The scale of “big–small” comprises one cluster (Figure 16.4 (a)). This means that all subjects evaluated all evaluation samples with similar scores on the “big–small” scale. In other words, we can say that the “big–small” scale of a product sound is a common scale where all subjects perceive in a similar manner. For such a SD scale, the conventional approach can be used where the average value is the representative value.

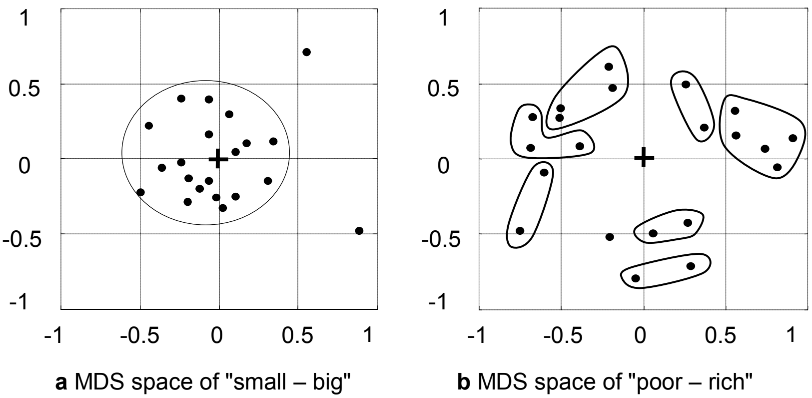

Figure 16.4 Examples of SD scales divided by correlation-based distance and cluster analysis. Each point represents a subject. The 2D space is composed by MDS: (a) MDS space of “small–big”, and (b) MDS space of “poor–rich”

The scale of “poor–rich” contains six clusters, indicating six different sensitivities (Figure 16.4 (b)). For such subjective SD scales containing different sensitivities, the average value should not be taken as a representative value because the average value might not be chosen by anyone. In fact, there are no data around the average value, which is the zero point of the space in Figure 16.4 (b). Thus, the average value of “poor–rich” represents nobody’s kansei.

Figure 16.5 shows the proportions of subjects included in each cluster for each SD scale. These proportions denote the commonalities of the divided SD scales. We discard clusters having only one subject because they represent extremely personal evaluation criteria.

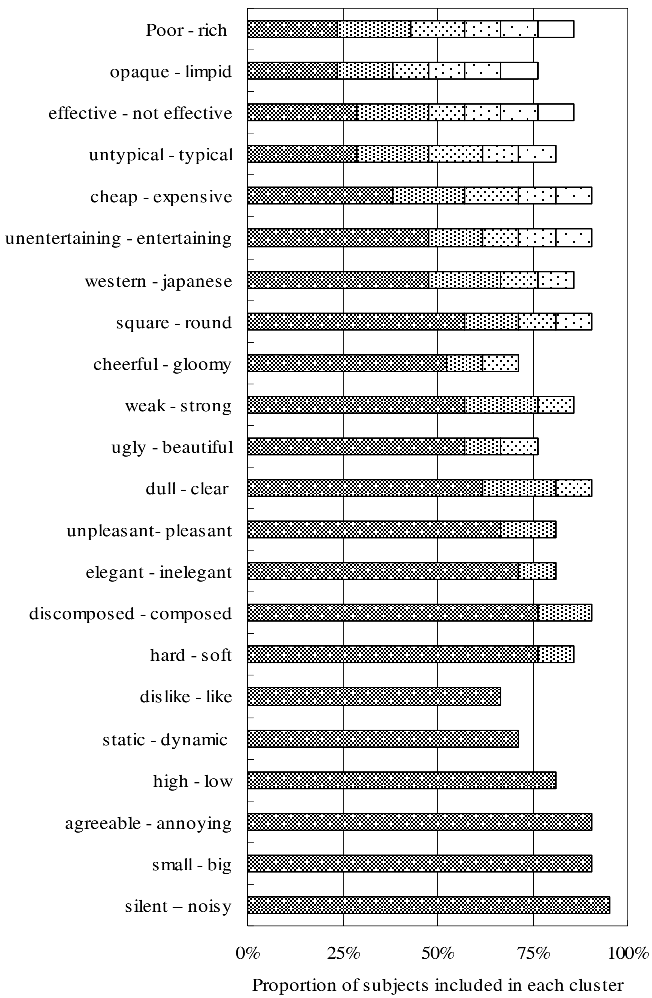

Figure 16.5 Proportion of subjects included in each cluster for all SD scales

The scales in Figure 16.5 are sorted by the number of divisions and commonality. For low-level perceptual scales, such as “silent–noisy”, “small–big”, and “low–high”, all subjects are grouped into one cluster. In other words, all subjects graded each sound sample in a similar manner and displayed similar sensitivity.

On the other hand, high-level impression scales, such as “cheap–expensive”, “effective–not effective”, and “poor–rich”, are divided into many clusters. Such highly subjective words contain multiple viewpoints of its cognition. These results suggest that commonality can be used as an indicator of the hierarchical order.

Some highly subjective scales, such as “like–dislike” and “pleasant–unpleasant”, even though they are assumed to contain different viewpoints that vary with individual subjects, are exceptions to the above rule, and are divided into only a few clusters. This result suggests that the commonality of highly subjective SD scales varies depending on the target design. For example, “like–dislike” is statistically similar among the subjects for the machine sound used in the experiment, although we can assume that the preference differs from person to person. Using the clustering method and commonality, the designer can extract such particular instances of divergent subjective scale characteristics.

16.5.4 Multiple Scales of a Target Kansei Quality

We use the SD scale “expensive–cheap” as a *target* kansei quality because we, as designers, believe that a luxurious sound increases a product’s emotional value. The target kansei quality is an SD scale that the designer temporarily sets as the design concept of the machine sound.

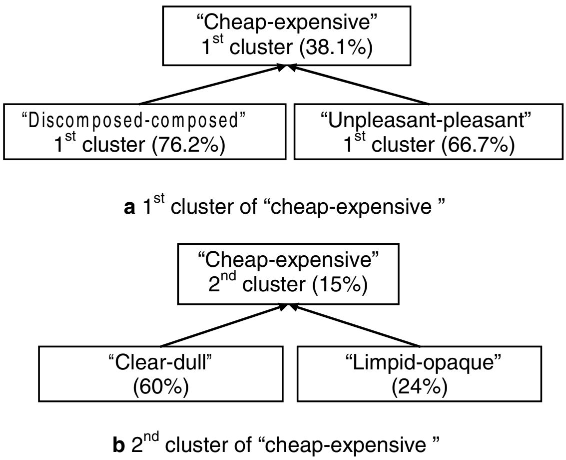

Figure 16.6 Semantic differences among multiple viewpoints of the target kansei quality “cheap–expensive” scale explained by correlations with other words whose commonality is higher: (a) first cluster of “cheap–expensive”, and (b) second cluster of “cheap–expensive”

The target kansei quality “expensive–cheap” contains five clusters, *i. e.*, five types of evaluation scales. Figure 16.6 shows an example of interpreting two different viewpoints of “cheap–expensive” using cluster scales of other words whose commonality is higher. The first cluster scale is related to the first clusters of “pleasant–unpleasant” and “composed–discomposed”, *i. e.*, the subjects who adopt the first scale perceive the “expensiveness” of the machine sound from the viewpoints of pleasantness and composedness. The second scale is related to the first clusters of “clear–dull” and “limpid–opaque”. The second scale is different from the first scale in terms of these semantics.

To consider the multiplicity of the definition of the target SD scale, we used the above two scales to set the design feature values of composite sounds.

16.5.5 Unexplored Design Area in Feature Space

We used SQM as the design features. To find untouched areas in the SQM space, we constructed a two-dimensional space using PCA. Figure 16.7 shows the result of PCA. The areas where no data appear are the untouched areas.

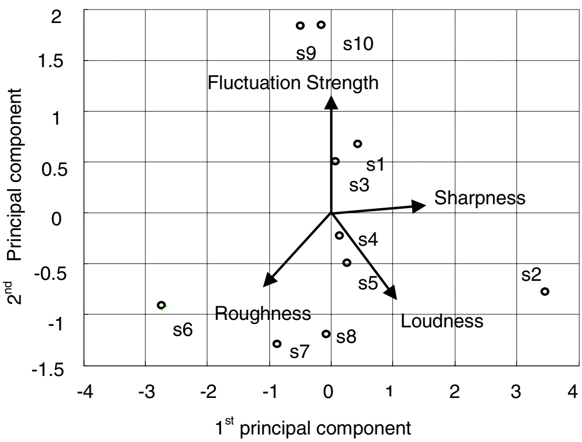

Figure 16.7 SQM space in low dimension constructed using PCA

16.5.6 Gradient of a Target Kansei Quality in Feature Space

To set design feature values in areas untouched by existing products, we need to establish the local gradients towards the target kansei quality along boundary areas between touched and untouched areas. If the target kansei quality has a nonlinear relationship with SQM, the regression plane derived from MRA using all data of existing products will not correspond to the gradient in the vicinity of the boundary areas. Furthermore, to cover multiple untouched areas, we should obtain multiple directions for setting features for creating composite sounds.

For the above reasons, we split the SQM space into several subspaces, each with the same number of sounds for existing products, and conducted an MRA for each split space.

Figure 16.8 shows regression planes of the first scale for “expensive–cheap” for each divided local area. The regression planes are represented in contour. The numbers on the contour lines denote the estimated value of the SD scale. According to the result, the gradients of all areas face in the same direction. The direction towards the upper left area is estimated as high in terms of the scale. Loudness and sharpness negatively relate to the scale. Meanwhile, we found three directions to increase the expensiveness of the sound in the second scale, as shown in Figure 16.9.

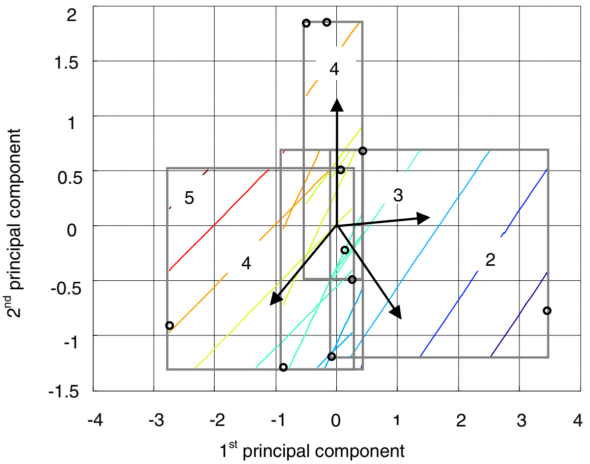

Figure 16.8 Example of local-regression surfaces of first cluster scale of “expensive–cheap”

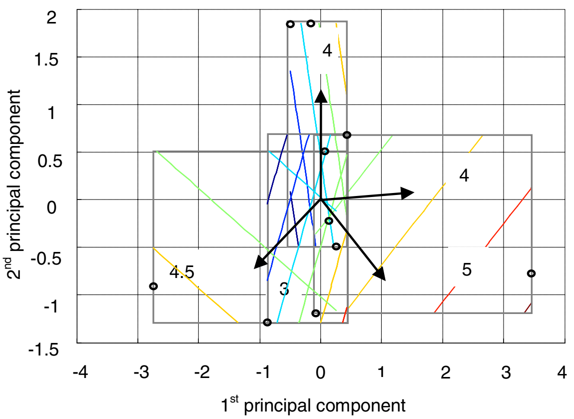

Figure 16.9 Example of local-regression surfaces of second cluster scale of “expensive–cheap”

16.5.7 Setting Feature Values and Creating New Sounds

By considering the obtained directions that increase the target kansei quality from the two major points of view and the untouched areas, we set the SQM values for creating sounds. We selected six original sounds from existing products and synthesized them so that they satisfied the above two conditions. The strategy of synthesizing sounds is based on increasing or decreasing the SQM values of the original sounds. We created 18 sounds as shown in Figure 16.10.

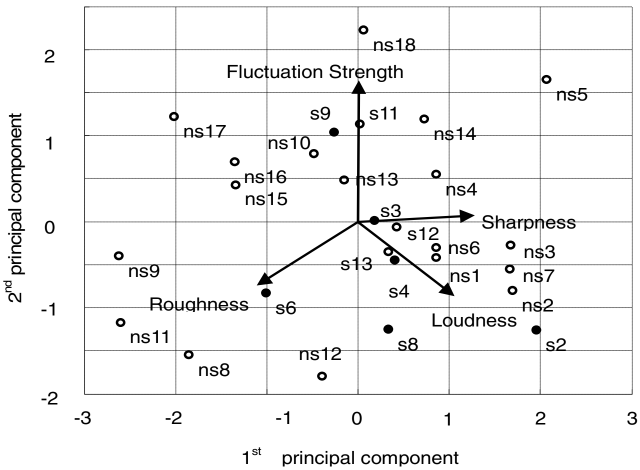

Figure 16.10 Original and composite sounds in SQM space

16.5.8 Sensory Test Using Composite Samples (Second Sensory Test)

We conducted the second sensory test using the created sounds and the original sounds. The purpose of the test is to find a potential evaluation factor that is effective for designing new sounds of a product. We used 18 created sounds and eight sounds of existing products as evaluation samples, all of which were stationary sounds. Thirty subjects, who were different to the subjects used in the first sensory test, evaluated the kansei qualities of each sound sample based on the SD method. We selected 11 SD scales (pairs of adjectives). We selected six SD scales – "cheap–expensive", "dislike–like", "agreeable–annoying", "silent–noisy", and "powerful–weak" – from the first sensory test and confirmed that they are independently effective SD scales. The remaining SD scales are newly introduced. The subjects were divided into three groups with ten people in each. The ten subjects listened to each sample using a headphone. Each sound was played for five seconds and the subjects evaluated the sounds, based on seven levels, by filling out a questionnaire consisting of word pairs.

16.5.9 Comparison of SD Scales Obtained from First and Second Experiment Data

First, we extracted patterns of personal SD scales from each SD scale using the proposed statistical method. In this method, we calculated correlation coefficients of the score vectors for each SD scale between subjects and conduct cluster analysis using the correlation coefficients to classify the subjects into groups of similar sensitivities. We used the average value of the SD scale in each cluster (group) as the representative score of the personal SD scale.

Figure 16.11 shows a comparison between the first and second sensory tests in terms of the proportion of subjects in each cluster for SD scales which are used in both tests. The proportions of the largest cluster for each scale (the black portion) are greater than 50% for both test results, except for the SD scale "expensive–cheap". The cluster that contains the largest proportion of subjects in a SD scale is called its "major cluster", and the scale that is composed of only the major cluster is called a "major scale". A major cluster represents a set of majority subjects who have a similar sensitivity for a SD scale.

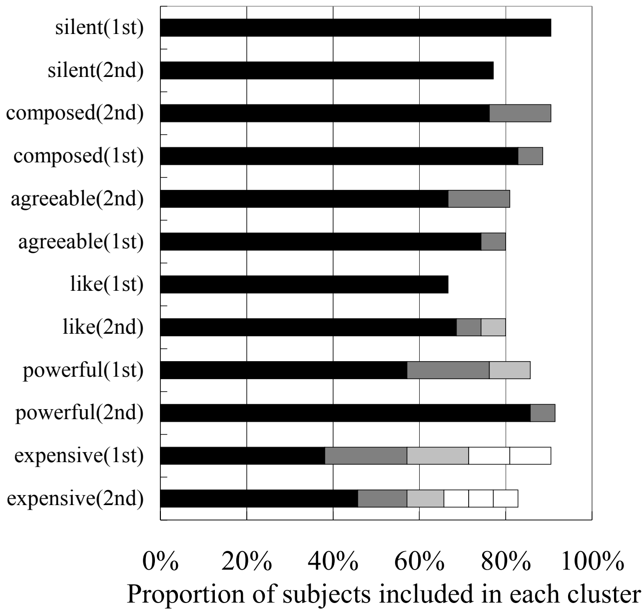

Figure 16.11 Comparison of proportion of subjects included in each cluster for SD scales that are used in first and second experiments

The target kansei quality "expensive–cheap" contains multiple SD clusters. The commonality of the major cluster is less than 50%. In other words, people have different sensitivities. To see the difference of semantics between SD cluster scales, we calculated the correlation coefficients between the top three SD cluster scales for "expensive–cheap" and the major scales of other SD scales. Table 16.2 shows the results. The three SD cluster scales of "expensive–cheap" all relate to the major scales of "composed–discomposed" and "silent–noisy". We found that only the SD scale "reliable–unreliable", which was newly introduced in the second test, discriminates the major scale from the other scales, as shown in Table 16.2. The SD scale "reliable–unreliable" contains two major scales.

Table 16.3 shows the correlation coefficients between the two cluster scales of "reliable–unreliable" and the major scales of other SD scales. The major scale of "reliable–unreliable", whose proportion is 31.4%, relates to "composed–discomposed" and "silent–noisy". The second cluster scale relates to "powerful–weak" and "unobstructed–obstructed". Those two feelings related to reliability have totally different contexts. The major cluster scale of "expensive–cheap" relates to both cluster scales of "reliable–unreliable". Only the third cluster scale relate to one of the scales of reliable. Thus, the major cluster scale of "expensive–cheap" is a complex scale that contains two different feelings of reliable sound.

Table 16.2 Correlation coefficients between SD cluster scales of "expensive–cheap" and related major scales

Expensive	Composed (82.9%)	Silent (77.1%)	Reliable (31.4%)	Reliable (28.6%)
Major scale (45.7%)	0.88	0.74	0.86	0.72
Second cluster scale (11.4%)	0.60	0.62	0.53	0.14
Third cluster scale (8.6%)	0.75	0.83	0.69	–0.06

Table 16.3 Correlation coefficients between SD cluster scales of "reliable–unreliable" and related major scales

Reliable	Composed (82.9%)	Silent (77.1%)	Powerful (85.7%)	Unobstructed (11.4%)
Major scale (31.4%)	0.95	0.90	–0.14	0.44
Second cluster scale (28.6%)	0.39	0.22	0.76	0.76

16.5.10 Finding Kansei Factors

The target SD scale "expensive–cheap" is a complex scale. To extract independent factors that are used to evaluate the sound quality of a product, we conducted a factor analysis using the SD cluster scales obtained from the results of the second sensory test.

Figure 16.12 shows the factor loadings of the first factor. The top three cluster scales of "expensive–cheap" all positively relate to the first factor. Only the major scale of "reliable–unreliable (31.4%)" relates to the first factor. Major scales related to it, such as “silent–noisy”, “composed–discomposed”, and “agreeable–annoying”, positively relate to the first factor.

Meanwhile, the second factor positively relates to the second cluster scale of “reliable–unreliable (28.6%)” and its related major scales such as “powerful–weak” and “unobstructed–obstructed”, as shown in Figure 16.13. The major scale of “expensive–cheap (45.7%)” relates to both factors, so that the factors are individual scales that can explain the complex feelings related to a sound’s expensiveness.

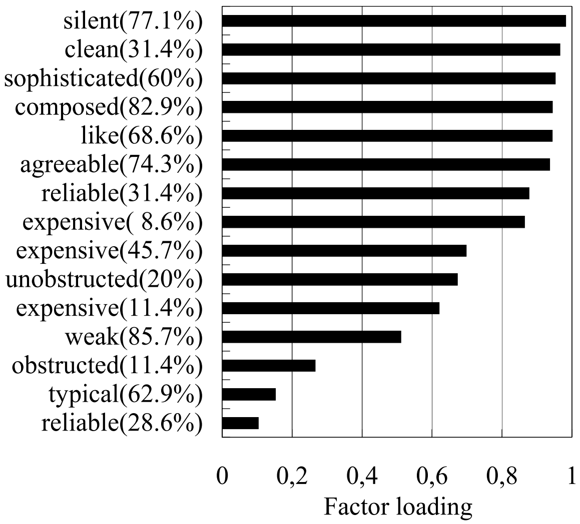

Figure 16.12 Factor loading of first factor (contribution ratio = 57.8%)

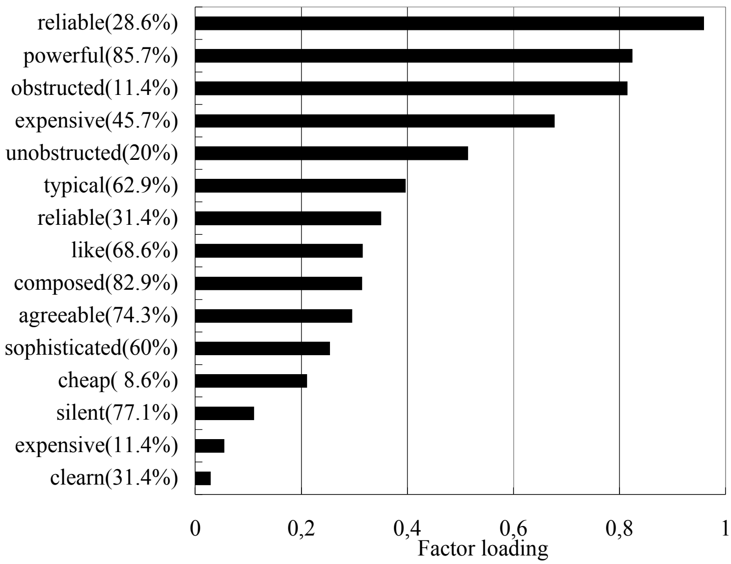

Figure 16.13 Factor loading of second factor (contribution ratio = 24.5%)

To formalize the factors, we conducted multi-regression analysis using the SQMs as explanatory variables. Table 16.4 shows the results of the analysis for the first factor. Both the regression coefficient and correlation coefficient of loudness are dominant. Loudness negatively relates to the factor. "Silent–noisy" has the highest factor loading, so that the value of the first factor increases when the sound is silent.

The fact that the first factor is related to loudness is adequate for conventional works that aim to reduce the loudness of the product sound. This factor represents a simple and clear goal when designing sound.

There is, however, a technical and cost limitation to reducing loudness. We focused on the second factor to design a sound without reducing loudness. The result of MRA using the second factor and SQMs shows that sharpness negatively relates to the factor, so that high-frequency sounds do not get higher scores for the factor. Loudness positively related to the factor, which means that reducing loudness reduces the evaluation score of the second factor. The first and second factors have a trade-off in terms of loudness. A measurable indicator, "tone-to-noise ratio" (TNR) [26], is newly introduced to explain the feelings of reliable and power-

Table 16.4 Result of multiple regression analysis using the first factor and SQM ($R = 0.87^{**}$)

SQM	Standardized regression coefficient	p	Partial correlation coefficient	Correlation coefficient
Loudness	–0.88	0.00	–0.87	–0.89
Sharpness	–0.15	0.27	–0.24	–0.66
Roughness	–0.07	0.40	–0.18	0.23
F.S.	–0.20	0.09	–0.35	–0.07

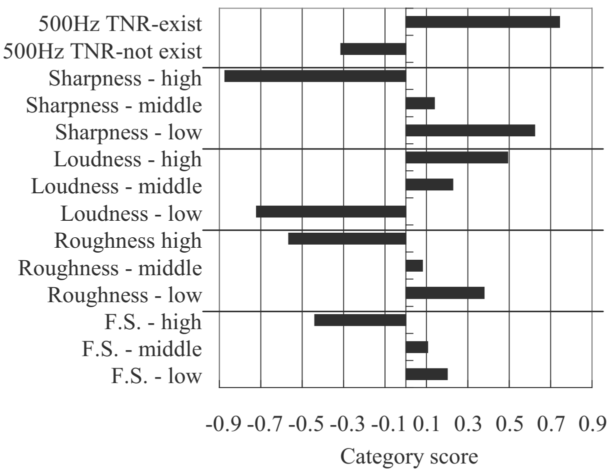

Figure 16.14 Results of quantification theory 1 using the second factor as an objective variable ($R = 0.9^{**}$)

ful, which highly relate to the second factor. The TNR is the difference between the tone and the sound pressure level of the noise in a critical band centered around the tone. Most vacuum cleaners have a peak tone around 500 Hz because of the frequency of the motor. We applied quantification theory using the TNR and SQMs as explanatory variables. Figure 16.14 shows the category scores, which represent the weights of each category of a feature. From the result, a sound having a perceivable TNR around 500 Hz gets high scores for the second factor. Thus we found that a perceivable motor sound is important to increase the second factor. This is a new criterion because conventional approaches have aimed at reducing TNR and loudness.

References

1. Yanagisawa H., Fukuda S.: Interactive reduct evolutionary computation for aesthetic design. Trans. AMSE J. Comp. Inf. Sci. Eng. **5**(1):1–7 (2005)
2. Maslow A.H.: A theory of human motivation. Psychol. Rev. **50**:370–396 (1943)
3. Osgood C.G., Suci G.J., Tannenbaum P.: The Measurement of Meaning. University of Illinois Press, Champaign, IL (1957)
4. Thurstone L.L.: The Measurement of Values. The University of Chicago Press, Chicago, IL (1959)
5. Hsiao S.W., Huang H.C.: A neural network based approach for product form design. Design Studies **23**(1):67–84 (2002)
6. Pawlak Z.: Rough sets. J. Comp. Inf. Sci. **11**:341–356 (1982)
7. Pawlak Z.: Rough classification. J Man-Machine Studies **20**:469–483 (1984)
8. Mori N., Takanashi R.: Knowledge acquisition from the data consisting of categories added with degrees of conformity – proposal of extended reduct calculation in rough set theory. Kansei Eng. Int. **1**(4):19–24 (2000)
9. Nakamori Y., Ryoke M.: Modeling of fuzziness in multivariate analysis. In: Proceedings of IEEE SMC Conference 2004, vol. 1, pp. 294–298 (2004)
10. Yanagisawa H., Fukuda S.: Development of industrial design support system considering customers’ subjective evaluation. Trans. Jpn. Soc. Mech. Eng. **68**(675):3431–3438 (2001)
11. Takagi H.: Interactive evolutionary computation. Proc. IEEE **89**(9):1275–1296 (2001)
12. Yanagisawa H., Fukuda S.: Development of interactive industrial design support system considering customer's evaluation. JMSE Int. J. Series C **47**(2):762–769 (2004)
13. Smyth S.N., Wallace D.R.: Toward the synthesis of aesthetic product form. In: Proceedings of ASME DETEC’00 Computers and Information in Engineering Conference (2000)
14. Yanagisawa H., Murakami T., Noguchi S. *et al.*: Quantification method of diverse kansei quality for emotional design – application of product sound design. In: Proceedings of DETC’07/ASME International 27th Computers and Information in Engineering (2007)
15. Yanagisawa H., Kataoka A., Murakami T. *et al.*: Extraction of latent emotional factors by analyzing human sensitivity towards unexplored design: application to product sound design. In: Proceedings of International Conference on Engineering Design 2009 (2009)
16. Yanagisawa H., Murakami T., Ohtomi K. *et al.*: A method for quantifying product emotional quality considering diversity of personal sensitivities. In: Proceedings of Design Engineering Workshop, pp. 102–107 (2008)
17. Zwicker E., Fastl H.: Psychoacoustics: Facts and Models, 3rd edn. Springer, New York (2006)
18. Otto N., Amman S., Eaton *et al.*: Guidelines for jury evaluations of automotive sounds. In: Proceedings of the 1999 SAE Noise and Vibration Conference (1999)

19. Chatterley J.J., Sommerfeldt S., Blotter J. *et al.*: Sound quality testing and analysis of multiple brands of sewing machines. In: Proceedings of ASME IDETC/CIE 2005 (2005)
20. Vastfjall D., Gulbpl M., Kleiner M. *et al.*: Affective evaluation of and reactions to exterior and interior vehicle auditory quality. J. Sound Vibration **255**(3):501–518 (2002)
21. Fastl H.: Neutralizing the meaning of sound for sound quality evaluations. Internoise (2001)
22. Ellermeier W., Zeitler A., Fastl H.: Predicting annoyance judgments from psychoacoustic metrics: identifiable versus neutralized sounds. Internoise (2004)
23. ISO 226: Acoustics – normal equal loudness level contours (2003)
24. ISO 532/R: Acoustics – method for calculating loudness level (1975)
25. Schiffman S.S., Reynolds M.L., Young F.W.: Introduction to Multidimensional Scaling. Academic Press, New York (1981)
26. ISO 7779 ANSI S1.13: Tone to noise ratio (1995)