INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED'09
24 - 27 AUGUST 2009, STANFORD UNIVERSITY, STANFORD, CA, USA

EXTRACTION OF LATENT EMOTIONAL FACTORS BY ANALYZING HUMAN SENSITIVITY TOWARDS UNEXPLORED DESIGN: APPLICATION TO PRODUCT SOUND DESIGN

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ABSTRACT
In the design of emotional qualities, which is evaluated by the customer's subjective impressions, feelings and emotions, one of the most important and difficult issues is setting quantitative evaluation criteria to evaluate such qualities. Without such evaluation criteria, the designer has to rely on his/her sensitivity, which may be different from the customer's, making it difficult to set a clear design goal. Most conventional approach formalizes emotional qualities expressed by adjectives using the sensory test with existing products. However, the variety of existing products is limited. The obtained evaluation criteria may not cover areas of a design space where future designs would appear. In this paper, we propose a method to cover such untouched area using composite design sample. We apply the method to extract a potential factor for the future design of product sound quality. To create such composite design samples, we set efficient design features that take into consideration the completeness of design space and the diversity of a target emotional quality that we quantify using the results of sensory tests with existing products. We conduct sensory test with composite design samples and compare the results with those from test with only existing product sound, in order to discuss changes introduced by adding composite samples. We extracted a new emotional scale of target emotional quality "expensiveness of machine sound" that was not found in the sensory test based only on the existing product sound. The emotional scale contains two different viewpoints of "reliable sound". One is associated with silent and composed sound and another is powerful and obstructed sound. Using a factor analysis considering the diversity of human sensitivities, we found those two viewpoints of "reliable sound" in first and second factors respectively. The first factor negatively related to loudness. The second factor related to lower sharpness and the existence of a perceivable peak tone around 500Hz. Most product makers are aware of the need to reduce loudness, i.e., the first factor. We extracted the second factor as a new evaluation criterion.

Keywords: emotional quality, design for machine sound, sound quality metrics, unexplored feature area, multivariate analysis.

1 INTRODUCTION
In the design of mature products, a product's emotional quality is becoming increasingly important due to diversifying customer's needs [1]. An emotional quality is a product quality that evokes a customer's specific impressions, feelings or emotions towards a product (e.g., comfort, luxury, delight). A product's sound is an important factor that affects the emotional quality [2]. For example, most people are annoyed by loud noises but become relaxed when hearing the sound of gentle waves. The task of the sound designer is to design a product sound that evokes a target emotion (impression) in the user.

The most important issue in the design of emotional 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 emotional 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 will misinterpret how a customer will evaluate his/her design.

To date, several studies have been carried out to extract such quantitative criteria of a product's emotional quality. The most common approach is using sensory tests and statistical methods. Most conventional approaches average the results of the sensory tests and compose a generalized relation with physical design attributes and features using statistical methods.
However, human sensitivities for emotional qualities differ from person to person. The range of individual differences depends on the particular emotional quality. Averaging the results of sensory tests to measure emotional quality is appropriate only when individual differences are negligible and most subjects share a similar sense. To address this issue of diversity, the authors proposed, in a previous work [3], a new emotional quantification method which pays special attention to the diversity of customers' sensitivities. Based on personal differences regarding sensitivity, the method extracts multiple emotional scales from SD scales, which are used in a sensory test called the semantic differential (SD) method[4]. An SD scale consists of a pair of adjectives representing an emotional quality, such as “powerful-weak”. We applied the method to construct evaluation criteria for the design of a cleaner sound using sound quality metrics (SQM) [5] as design features.
We constructed the evaluation criteria for emotional qualities using sound samples recorded from existing products and their emotional evaluations scored by human subjects. However, the variety of existing products is limited. The sounds of existing products may not be exhaustive enough in the design space to construct general evaluation criteria that can be used for future design. People may evoke different sensitivities towards an unknown sound.
The aim of this study is to extract and formalize evaluation criteria of emotional qualities that can be used for the future design of product sounds. To cover feature areas untouched by existing products in the design space, we create composite sounds synthesized from the original sounds of existing products. The strategy for creating such sounds is to disperse them on a target emotional quality and on untouched areas of the design feature space. To create composite sounds, we consider the diversity and nonlinearity of the customers’ sensitivities. We conduct a sensory test using both the composite and original sounds (existing product sounds) as evaluation samples. We discuss repeatable evaluation criteria. Using a factor analysis, we extract potential evaluation factors and discuss their importance in the future design of vacuum-cleaner sounds.

2 RELATED WORKS

2.1 Design for emotional quality

Emotional qualities are often represented by subjective words such as adjectives. Several methods employing sensory tests have been used to evaluate a product’s emotional quality represented by words. The SD method, which is widely used, uses pairs of opposite words to evaluate the emotional quality of 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[6] 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 emotional quality. Although this method enables one to precisely measure emotional qualities, the number of trials increases exponentially with the number of samples because of the possible combinations.
Most approaches to sensitivity quantification aim to make generalizations of sensitivity by averaging the subjects’ evaluations. A mapping between the averaged emotional score and measurable design attributes is composed. Several mapping methods have been developed and used, such as multi regression analysis, fuzzy reasoning, and neural networks[7]. The mapping serves as a metric of general emotional 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 [8] applies fuzzy set theory to represent sensitivity individuality. 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 with this method.
Yanagisawa et al. [9] found semantic differences of emotional words between the designer and customer using the SD method and principal component analysis (PCA). An emotional word contains multiple scales of semantics that vary with each person. There is not much point in averaging between

scales having different meanings. An averaged emotional quality cannot be used to represent diverse sensitivities.

Yanagisawa et al. proposed a method to extract multiple scales from an SD scale, when the SD scale consists of multiple sensitivities that differ from person to person[3]. In the method, we calculate the correlation coefficient between values of the SD scale of evaluation samples scored by two subjects. We regard the correlation coefficient as the similarity of sensitivity between subjects in terms of the SD scale. Using cluster analysis, we construct groups called SD clusters in which the similarities among members are high. The average value of each group is used as the representative value of that group. The semantics of an SD cluster is interpreted by its statistical relations with physical design features and other SD scales.

2.2 Product sound quality

One of the important factors that affect a product's emotional quality is the sound made by the product. For quite a long time, sound engineering mainly dealt with the reduction of the overall sound pressure level (SPL) emitted by a product. Within the last decade, however, the focus started to switch more towards aspects related to the quality of the sound. The biggest change is that the design goal switched from objective values, such as the "decibel" levels that can be physically measured, to subjective ones such as emotional qualities. To design such emotional qualities of product sound, it is necessary to develop metrics to quantitatively evaluate such subjective qualities. Zwicker et al. developed SQM as an evaluation metric of the product sound quality. SQM provides values for simple perceptions of sound such as loudness, sharpness, roughness and fluctuation strength [5]. However, product emotional qualities include more complex affective perceptions, such as pleasant, annoying, luxurious, etc. To deal with such complex sensitivity in sound design, most conventional approaches conduct sensory tests using affect-laden words to score target emotional qualities. Statistical methods are used to compose a map between SQM and complex emotional qualities[10]. Several applications have been studied based on the approach[11]-[14]. Most research so far, however, has not considered the diversity and potential of human sensitivity.

3 A METHOD FOR EXTRACTION OF LATENT EMOTIONAL FACTORS BY ANALYZING HUMAN SENSITIVITY TOWARDS UNEXPLORED DESIGN

3.1 Flow of method

The method consists of two sensory tests. The first sensory test uses evaluation samples of products existing on the market. The second test uses both composite samples and existing samples. We create the composite samples based on an analysis using results of the first sensory test. The procedure of the method is following.

(1) We prepared design samples from existing products that are available on the market. Using the samples, we conducted a sensory test based on the SD method. In the test, multiple subjects gave their impressions towards the samples using pairs of opposite adjectives, which are called SD scales. (2) Next, we extracted the design feature values from each sample. (3) From the results of the 1st 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. We have developed a method to extract such patterns using cluster analysis, based on the correlation coefficients between subjects for each SD scale as similarities of sensitivity. We formulated each extracted scale using the design features and interpreted the semantics of each subjective scale. (4) Based on the formulated scale, we set feature values that are used to synthesize composite design samples. We select an SD scale as the target emotional quality and set feature values so that they are dispersed on the scale. To extract emotional criteria that can be used for future design, the design feature values must cover areas of the feature space untouched by existing product. We synthesize composite design samples to fit the set feature values by editing the original samples of existing products.

(5) We conduct a 2nd sensory test using both created samples and existing ones in the same manner as the 1st sensory test. For the SD scales, we add new SD scales to or delete old ones from the 1st sensory test based on their contribution. (6) We extract and formulate multiple scales from the result.

(7) To see the repeatability of the scale, we compare the results of the 1st and 2nd sensory tests in terms of the SD scales commonly used in both experiments. We analyze the changes in emotional

quality due to the addition of new composite design samples. Finally, we extract potential factors of the emotional evaluation criteria for designing new samples. We apply factor analysis using the multiple scales obtained from the results of the 2nd sensory test.

3.2 Extraction of multiple emotional scales considering its diversity

We select N_p products Si (I = 1,2,…,N_p) as evaluation samples of the sensory test. N_s subjects T_j (j = 1, 2, …, N_s) evaluate their impressions of the samples S_i using the SD method with N_w pairs of emotional words (scales) I_k (k = 1, 2, …, N_w). Let $E_{jk} = < e_{ijk} >$ be a vector of scores given by the j^{th} subject for all evaluation samples in terms of I_k. If the p^{th} subject has a similar sensitivity to the q^{th} subject in the SD scale I_k, the correlation coefficient of E_{pk} and E_{qk} should be close to 1.0. If the p^{th} subject has the opposite sensitivity to the q^{th} subject for I_k, the correlation coefficient should be close to -1.0. We define the distance between the p^{th} and q^{th} subjects in terms of the sensitivity of an emotional word I_k as follows:

$$d_{kpq} = 1 - r(E_{pk}, E_{qk}) \qquad (p \neq q) \qquad (1)$$

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

For each SD scale, we 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 *kansei* scale with significance level α. If an emotional word is objective and most subjects have similar sensitivities, the number of clusters should be low. If all of the subjects have similar sensitivities regarding the SD scale, the scale remains undivided. We define the *commonality* of an emotional word for each cluster as follows:

$$com_l = \frac{\#Tc}{\#T} \times 100 \qquad (Tc \in C_l) \qquad (2)$$

where $\#T$ denotes the number of subjects and $\#Tc$ denotes the number of subjects included in the l^{th} cluster C_l. The *commonality* is equal to 1.0 if all subjects have a similar (statistically same) sensitivity of the SD scale. A low-*commonality* cluster may represent a rare sensitivity possessed by only a few people. We use the *commonality* as an indicator of subjectivity. We use the average value of each cluster as a central value of the cluster.

3.3 Setting design feature values of composite design samples

There are two strategies for creating composite design samples, as follows. The first strategy is to create design samples in the 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 dimension of features is more than three, it is difficult to visually find such areas. To reduce the dimensions of features, we apply principal component analysis (PCA). PCA reduces a multidimensional space into a lower-dimensional space (2D or 3D) while retaining as much information as possible. We extract N_f design features $P = <p_1, p_2, …, p_{Nf}>$ for the evaluation samples of the sensory test. The i^{th} principal component F_i is obtained as follows:

$$F_i = W_i' P \qquad (3)$$

where, $W_i = < w_1, w_2, …, w_{Np} >$ 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.

The second strategy is to set a target emotional 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 extract latent factors for such quality. To set such design features, we formalize a target emotional quality using the results of the 1st sensory test. Assume we obtain *Nc* clusters from the target emotional quality. We apply multiple regression analysis(MRA) [10] to formalize the target emotional quality for each cluster, using extracted design features as explanatory variables. The central value of the l^{th} cluster $Y_l = <y_{l1}, y_{l2}, \ldots, y_{lNs}>$ is estimated as follows:

$$Y_l = A_l' F + \beta \qquad (4)$$

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 emotional quality.

4 EXTRACTION OF LATENT FACTORS FOR PRODUCT SOUND QUALITY

Using the proposed method, we attempt to extract latent evaluation factors of product sound quality, which can be used for future design.

4.1 Sensory test using existing samples: 1st sensory test

The authors carried out a sensory test using existing sound samples in our previous work. Here we use those results. We recorded the stationary sounds from ten selected products of different makers in an anechoic chamber and used them as evaluation samples. We selected 23 pairs of emotional words related to the target product sounds. The subjects listened to each sound for five seconds and gave their impressions of the sounds by filling out a questionnaire consisting of word pairs (SD method-based test). To avoid the influence of the learning curve, the subjects practiced responding before conducting the experiment.

4.2 Finding feature area unexplored by existing products

We use SQM as the design features. To find untouched areas in the SQM space, we construct a two-dimensional space using PCA. Figure 1 shows the result of PCA. The areas where no data appear are the untouched areas.

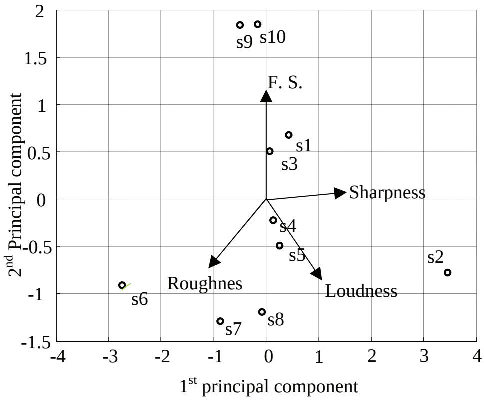

Figure 1 SQM space in two dimension constructed using PCA

As for strategy, we select a target emotional quality. The target emotional quality is an SD scale that the designer temporary sets as the design concept of the machine sound. For example, in this paper, we select “expensive – cheap” as a target emotional quality because we, as designers, believe that a luxurious sound increases a product’s emotional value. (It is assumed that the target emotional quality has a high priority in the customer's evaluation of the product sound) To set SQM values dispersed on the target emotional quality we formalize its evaluation criteria using the SQM values as the explanatory variables. Because such subjective quality is different from person to person, we extract patterns of different scales from an SD scale based on personal differences. We apply the method proposed in our previous work to extract those multiple scales. We then formalize each scale using MRA. We split the SQM space into local spaces and apply MRA for each local space. By conducting MRA for each local area, we obtain the gradients at each boundary region between the touched and untouched areas.

4.3 Setting feature values dispersed on the target emotional quality

We use the SD scale "expensive-cheap" as a target emotional quality. In our previous study, we extracted two different scales from the SD scale by analyzing the results of the 1st sensory test using the proposed method[3]. In other words, each subject has a different sensitivity towards the SD scale "expensive-cheap" and we extracted two patterns of personal emotional criteria that can be explained using SQM, which are the design features.

The first scale is related to "pleasant-unpleasant" and "composed-discomposed". Namely, the subjects who adopt the first scale perceive the "expensiveness" of the machine sound from the viewpoints of pleasantness and composedness. Loudness and sharpness negatively relate to this scale, so that an expensive sound should be silent in this viewpoint. The second scale that can be formalized using SQM is related to "clear - dull" and "limpid-opaque". This expensiveness relates positively to loudness. 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 use the above two scales to set the design features of composite sounds.

In the previous work, we used MRA to quantify the SD scale by design features. MRA is useful for grasping holistic linear relations of cause and effect. Yet, to set features in areas untouched by existing products, we need to establish the local gradients around the boundary areas between touched and untouched areas. If the target SD scale has a non-linear relation with SQM, the regression plane of MRA does not correspond to the gradient in the vicinity of boundary areas. Furthermore, to cover multiple untouched areas, we should obtain multiple directions for setting features for creating composite sounds. From the above reasons, we split the SQM space into several subspaces, each with the same number of sounds of existing products, and conduct a MRA for each split space.

Figure 2 shows the regression plane of the first scale for "expensive-cheap" in SQM space. The regression plane is represented in contour. The number on each contour line denotes the estimated value of the emotional 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 3.

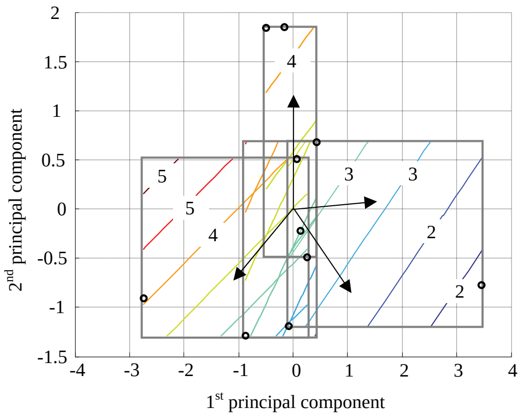

Figure 2 Example of local-regression surfaces of SD word "Expensive-cheap(38.1%)"

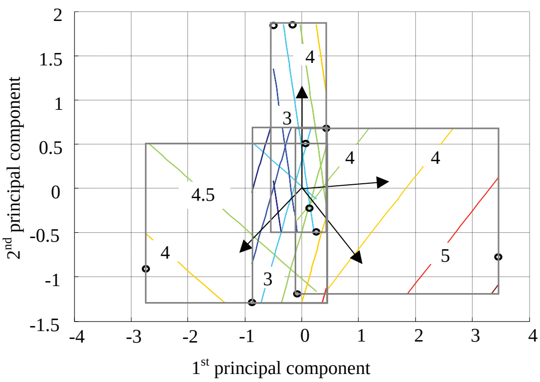

Figure 3 Example of local-regression surfaces of SD word "Expensive-cheap(14.3%)"

4.4 Creating new sounds

By considering the obtained directions that increase the target emotion from two major points of view and the untouched areas, we set the SQM features for creating sounds. We selected six original sounds from existing products and synthesize them so that they satisfy the above two conditions. The strategy of synthesizing sounds is based on increasing or decreasing the SQM features of the original sounds. We created 18 sounds represented as filled circles in figure 4.

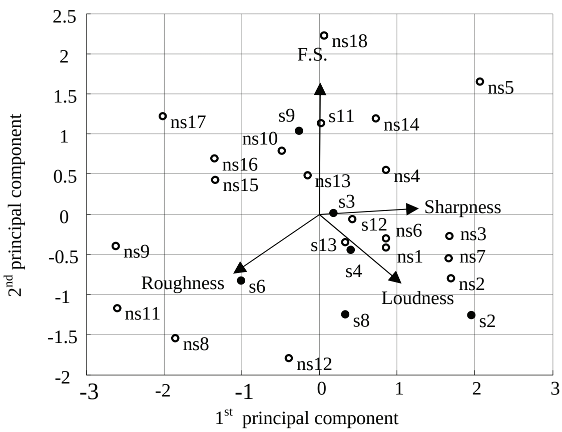

Figure 4 Original and composite sounds in SQM space

4.5 Sensory test using composite sounds (2nd sensory test)

We conduct the 2nd sensory test using the created sounds and the original sounds. The purpose of the test is to find a potential emotional factor that is effective for designing new sounds of a product.

We use eighteen created sounds and eight sounds of existing products (six original sounds and three newly recorded sounds) as evaluation samples. All of them are stationary sounds. 30 subjects, who are different from the 1st sensory test, evaluate the emotional qualities of each sound sample based on the SD method. We selected 11 SD scales (pairs of adjectives) as shown in table 2. We selected six SD scales – "cheap-expensive", "dislike-like", "agreeable-annoying", "silent-noisy" and "powerful-weak" – from the 1st sensory test. We confirmed that they are independently effective SD scales. The remaining SD scales are newly introduced.

We divide the subjects into three groups of ten people each. The ten subjects listen to each sample using a headphone. We play each sound for five seconds and the subjects give their impressions of the sounds, based on seven levels, by filling out a questionnaire consisting of word pairs. We insert white noise of 50kHz between each sound sample to avoid context effects. To avoid the influence of the learning curve, the subjects practice responding before conducting the experiment.

Table 1 SD words used in the 2nd sensory test with SD method

No.	**Pair of SD words**
1	cheap – expensive
2	dislike – like
3	discomposed - composed
4	distinctive – common (sounds like a machine)
5	Reliable – Unreliable
6	agreeable - annoying
7	sophisticated – unsophisticated
8	(exhaust air sounds) clean – dirty
9	silent – noisy
10	powerful – weak
11	(Exhaust air is) unobstructed-obstructed

5. RESULTS AND DISCUSSION

5.1 Comparison of emotional scales obtained from 1st and 2nd experiment data

Firstly, we extracted patterns of personal emotional scales from each SD scale using a statistical method proposed in our previous work[3]. In this method, we calculate 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 use the average value of the SD scale in each cluster (group) as the representative score of the personal emotional scale.

Figure 5 shows a comparison between the 1st and 2nd 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 (black portion) are greater than 50% for both test results except for the SD scale “expensive-cheap”. We call such clusters that contain the largest proportion of subjects “major clusters” and call scales that are composed of major clusters major scales. A major cluster denotes a set of majority subjects who have a similar sensitivity for a SD scale.

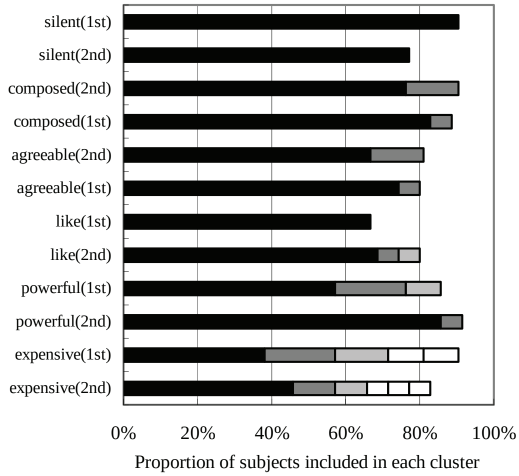

Figure 5 Comparison of proportion of subjects included in each cluster for SD scales which are used in 1st and 2nd experiment

Table 2 represents the correlation coefficients between major scales obtained from the 1st and 2nd sensory tests for each SD scale used in both tests. The percentage figures in parentheses represent the proportions of the respective major clusters. To calculate the correlation, we used the SD score of the original sounds used in both tests. Most of the correlation coefficients are statistically significant at the 95% significant level. Although the SD scale "like-dislike" is not significant, the correlation coefficient is high (r = 0.79). Thus, the scores of the major scales for the SD scales are statistically the same even though the subjects have been changed.

Table 2 Correlation coefficients (r) between major scales of 1st and 2nd sensory test

1st sensory test	**2nd sensory test**	***r***	***p***
silent(90.5%)	silent(77.1%)	0.87	0.02
composed(76.2%)	composed(82.9%)	0.83	0.04
powerful(57.1%)	powerful(85.7%)	0.85	0.03
like(66.7%)	like(68.6%)	0.79	0.06
agreeable(66.7%)	agreeable(74.3%)	0.87	0.03
expensive(38.1%)	expensive(45.7%)	0.83	0.04

The target SD scale "expensive-cheap" contains multiple SD clusters. The proportion 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 calculate the correlation coefficients between the top three SD cluster scales for "expensive-cheap" and the major scales of other SD scales. Table 3 shows the results. All SD cluster scales of "expensive-cheap" relate to major scales of "composed-discomposed" and "silent-noisy". We found that only the SD scale "reliable-unreliable", which we newly introduced in the 2nd test, discriminates the major scale from the other scales, as shown in table 3. The SD scale "reliable-unreliable" contains two major scales.

Table 3 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%)	<u>0.88</u>	<u>0.74</u>	<u>0.86</u>	<u>0.72</u>
2nd cluster scale (11.4%)	<u>0.60</u>	<u>0.62</u>	0.53	0.14
3rd cluster scale (8.6%)	<u>0.75</u>	<u>0.83</u>	<u>0.69</u>	-0.06

Table 4 shows correlation coefficients between the two cluster scales of "reliable-unreliable" and 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 (28.6%) 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 3rd cluster scale relate to one of the major scales of reliable. Thus, the major cluster scale of "expensive-cheap" is a complex scale that contains two different feelings of reliable sound.

Table 4 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%)	<u>0.95</u>	<u>0.90</u>	-0.14	0.44
2nd cluster scale (28.6%)	0.39	0.22	<u>0.76</u>	<u>0.76</u>

5.2 Finding emotional 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 conduct a factor analysis using the SD cluster scales obtained from the results of the 2nd sensory test.

Figure 6 shows the factor loadings of the first factor. All cluster scales of "expensive-cheap" 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 2nd cluster scale of "reliable-unreliable(28.6%)" and its related major scales such as "powerful–weak" and "unobstructed-obstructed", as shown in figure 7. The major scale of "expensive-cheap (45.7%)" relates to both factors, so that the factors are individual scales to explain the complex feelings related to a sound's expensiveness.

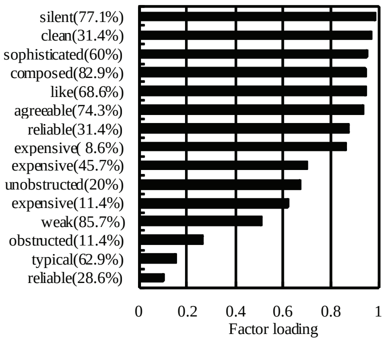

Figure 6 Factor loading of 1st factor (contribution ratio=57.8%)

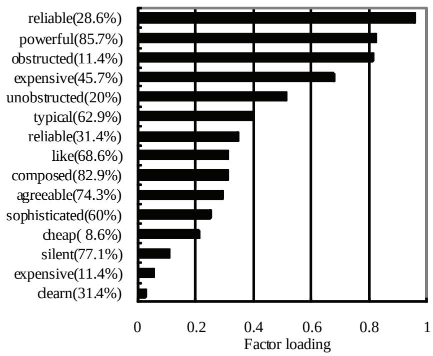

Figure 7 Factor loading of 2nd factor (contribution ratio=24.5%)

To formalize the factors, we conduct multi-regression analysis using the SQMs as explanatory variables. Table 6 shows the results of the analysis. Both the regression coefficient and correlation coefficient of loudness are dominant. Loudness negatively relates to the 1st factor. "Silent-noisy" has the highest factor loading, so that the value of the 1st factor increases when the sound is silent.

The fact that the 1st 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 focus on the 2nd factor to design a sound without reducing loudness. Table 7 shows the result of MRA using the 2nd factor and SQMs. 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. It means that reducing loudness reduces the evaluation score of the 2nd factor. The 1st and 2nd factors have a trade-off in terms of loudness.

*Table 5 Result of multiple regression analysis using the 1st 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

*Table 6 Result of multiple regression analysis using the 2nd factor and SQM (R=0.74**)*

SQM	standardized regression coefficient	p	partial correlation coefficient	correlation coefficient
Loudness	0.53	0.00	0.6032	0.29
Sharpness	-0.76	0.00	-0.6677	-0.51
Roughness	-0.29	0.02	-0.4749	-0.18
F.S.	-0.25	0.12	-0.3286	-0.76

However, the SQMs are not enough to express the feelings of reliable and powerful, which highly relate to the 2nd factor. We newly introduce a measurable indicator "tone-to-noise ratio (TNR)" to explain this. The TNR is the difference between the tone and the sound pressure level of the noise in a critical band centered around the tone[17]. If TNR exceeds 6db the tone is prominent. Most vacuum cleaners have a peak tone around 500Hz because of the frequency of the motor. We apply quantification theory using the TNR and SQMs as explanatory variables. Figure 8 shows the category scores, which represent the weights of each category of a feature. From the result, a sound having a perceivable TNR around 500Hz gets high scores for the 2nd factor. Thus a perceivable motor sound is important to increase the 2nd factor.

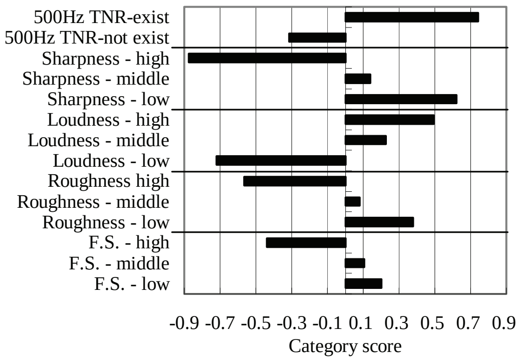

*Figure 8 Results of quantification theory I using the 2nd factor as an objective variable (R=0.9**)*

CONCLUSION

In this work, we proposed a method for extraction of potential emotional factors by analyzing human sensitivity towards unexplored design and applied the method for designing product sound quality. To set a clear direction for the future design of a product sound as one of emotional qualities, we created composite sound samples that cover areas of the design space untouched by sounds of existing products. We set a target emotional quality, which is "expensiveness", and used it to create composite sounds and achieve completeness of the data in the feature space. We used multiple emotional scales of the target emotional quality obtained from the 1st sensory test, which was based on the SD method and conducted using sounds of existing products. We conducted the 2nd sensory test in which a different group of subjects evaluated the emotional qualities of sound samples, including both the original sounds of existing products and the composite sounds. The results obtained are follows:

- The proportions of SD clusters representing the degree of diversity are similar in the results of the 1st and 2nd sensory tests.
- Correlation coefficients between majority scales obtained from the two sensory tests are statistically significant in terms of common SD scales except for "expensive-cheap". Thus, the human sensitivity expressed by such SD scales is repeatable.
- Only the SD scale "expensive-cheap" involves multiple SD clusters. This means that the sensitivity of the SD scale varies from person to person.
- The major scale of "expensive-cheap" contains two different factors using factor analysis. The first factor negatively related to the loudness SQM. The second factor related to a lower sharpness SQM

and also to the existence of a perceivable peak tone around 500Hz, which corresponds to the frequency of the inside motor.
The first factor is a trivial solution because the majority of makers aim to reduce the sound loudness. On the other hand, the second factor is a new criterion useful for evaluating and designing new sounds of a product.

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