Quantitative evaluation of sensitivity in confidential car exterior design

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ABSTRACT

In recent years, the manufacturing industry has seen a shift in competition from performance, which can easily be evaluated numerically, to design which much more challenging to express numerically. The rise of companies that focus on design, such as Apple, Samsung, and IKEA, is remarkable. However, design presents two challenges for the manufacturing industry. First, the sensory aspect of design is challenging to evaluate quantitatively, and unified evaluation indicators are not yet defined. Second, confidentiality of product design. In many cases, the design is kept in confidence within the companies, so it is often hesitated to investigate large customers. The above two problems increase the influence of the evaluator’s experience and cause a situation that it is challenging to create a design desired by the customer. Therefore, the present study aims to enable inexpensive quantitative evaluation of automobile exterior design while maintaining confidentiality. We propose a technique that uses a convolutional neural network to link features extracted from accumulated design images to the sensitivity extracted from the customer’s voice. This is then used to quantitatively evaluate an input image.

Key Words: Emotional value, Design engineering, Deep learning, Natural language processing

1. INTRODUCTION

Japanese companies have manufactured world-leading weapons and other high-technology products to high standards of quality and performance. Despite maintaining these high technological standards, strong sales performance has not necessarily followed, and many manufacturing companies are now struggling. In contrast, companies that emphasize design, such as Apple, Samsung, IKEA, and Dyson, are performing well.[1]

As technological development progresses, product performance and quality exceed customer needs and overshoot occurs. Overshoot occurs when excessive competition leads to improvements in function and specification that do not affect the utility to customers. Therefore, in the market for the product, commoditization and price competition occur. In addition, further investment in technological development is ineffective for the manufacturers of such products.[1]

Performance and quality of products can be expressed numerically, and these specifications can be easily published. These are called functional values. To contrast with functional value, emotional value can be evaluated by human sensitivity, such as concept, customer experience, or design. Once overshoot has occurred in functional value, it is necessary to improve emotional value to avoid price competition of goods, to add value to products, and to maintain market competitiveness.
The most important factor in quickly judging the appeal of a product is the design, which customers can assess in as little as in 0.05 s.\cite{2} Companies that emphasize emotional value, especially design, such as IKEA, Apple, Samsung, and Dyson, are emerging in the global market and rapidly taking market share from Japanese companies.

There are three main problems when assessing whether a design is good or bad. The first problem is that it is challenging to quantitatively evaluate design because accounting costs of design are not defined, and a unified evaluation index has not been defined yet. In Kansei engineering, predefined viewpoints are typically evaluated using five- to seven-point Likert scales according to the semantic differential (SD) method developed by Osgood.\cite{3} The second problem is maintaining the confidentiality of a product design. Designs are often highly guarded secrets for companies, and it is challenging to gather customer opinions on a design while maintaining this secrecy. Therefore, internal expert evaluators often assess designs using methods such as the SD method. Therefore, instead of large-scale surveys, neuroscience approach such as functional magnetic resonance imaging (fMRI) and Electroencephalograph (EEG) are getting popular because we can understand the sensitivity precisely with evaluation of few subjects. Li et al. proposed an evaluation method for uniqueness of product appearance by EEG equipment and an eye-tracking device to record a subject’s brain activity and eye-gaze data.\cite{4} However, this leads to the third problem: that dedicated facilities are required and subject’s load is high, resulting in high costs. Thus, it is still challenging to evaluate many times at the site of design.

Therefore, in the present study, we propose a method to evaluate the sensitivity of new car exterior designs using accumulated designs and the customer’s opinions without revealing the design to be evaluated.

2. EVALUATION OF PRODUCT DESIGN

2.1 Understanding the characteristics and impressions of design

Ryoke et al. prepared 30 samples for the survey.\cite{5} These were evaluated using the SD method using 26 pairs of adjectives with a seven-point Likert scale for each pair. The obtained results allowed the authors to quantify the association between the adjectives and the sample. Sato considered the construction of design clusters and their characteristics based on the impression evaluation results for the front grille design of an automobile.\cite{6} Ten front grille designs were investigated with respect to 14 impressions such as “cute” and “fashionable”. The results were analyzed using quantification theory class III. A cluster similarity map was constructed by cluster analysis, as shown in Figure 1. As an example of how the map is used, group 4 is the closest to “vintage”, and designs close to the impressions “natural” or “adult” have a common feature in that they use wood grain.

These approaches are suitable for understanding the emotional aspects of design characteristics and impressions. However, evaluations that maintain the confidentiality of new designs have not been investigated.

![Figure 1. Similarity map of front grille designs](image-url)
2.2 Causal relationship between morphological elements and images by rough set analysis

Unlike specifications in which each function can be numerically evaluated, design needs to be evaluated as a comprehensive whole with many interrelated attributes. Thus, it is important to understand not only the trend but also factors including combination synergy and offset effect. Therefore, rough set theory can be used to acquire valuable information on emotional design.

Inoue et al. revealed the causal relationship between form elements, attributes and images using rough sets for the front mask design of cars.[7] The form factor and attribute “shape of air intake” was evaluated as a negative influence by correspondence analysis. However, rough set analysis it was shown that a combination of “the internal structure of the light stands out” and “the grill is thin” contributes to a positive influence.

However, the rough set approach requires a huge number of validations when covering all combinations of form elements and attributes, which is unrealistic. In the above study, two to three attributes are prepared for each of the eight elements, each of which has 4,374 combinations, but these were evaluated with only 17 samples. In actual designs, the numbers of form elements and attributes become enormous, so it is difficult to efficiently extract meaningful results. In other words, we should explore methods in which humans do not define feature quantities of design elements. Nevertheless, there are still few proposals for the method of customer’s sensitivity in product design.

Li et al. proposed a method to optimize the design of product form based on supporting vector and artificial fish swarm algorithm in order to meet customers’ demand for perceptual cognition of product form. However, in this verification targeting refrigerators, 10 critical control points have been set, and it is necessary for humans to designate feature quantities.[8] Yang et al. validated that multiple regression analysis based on design elements and perceptual image helped designers design car console which could meet users’ psychological needs. However, for example, navigation radio panels are three types of square, polygon, and arc line, so that humans have to define the design elements as well.[9]

2.3 Feature value extraction by deep learning

It is unrealistic for humans to set all feature quantities. Therefore, recent studies have used deep learning for extracting features from images. A competitor in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2015, an international competition for computer object recognition, reached a human-level accuracy of feature identification, exceeding 5.1%.[10] Schroff extracted features from images of human faces with 22 layers of deep learning and succeeded in identification of individuals with an accuracy of 99.63%.[11] Karpathy et al. extracted features and behaviors from photographs and used this information generated descriptive texts.[12] Mansimov et al. extracted information from sentences, including adjectives describing colors and states, and generated images.[13] However, in these studies, objects, colors and actions that are not blurred by humans are considered objects, and they do not have features that are not clearly defined. Under these circumstances, Shimoda et al realized the perception of texture of things.[14]

In the Japanese language, there are a lot of onomatopoeic words that expresses the state of things. For example, the word pom-pom in Japanese is used to describe something that is round and bulging. By extracting vocabulary features using a convolutional neural network (CNN), the images of Figure 2 are obtained. The accuracy of the CNN in identifying images that match onomatopoeic words was 84.6%.

Although humans were released from work that defines the feature quantity by deep learning, there are few proposals for estimating customer’s sensitivity in product design.

![Figure 2. Image example of flowers obtained by onomatopoeic terms](image)

3. METHODS

3.1 Outline of this research

In this research, we proposed a technique to quantitatively evaluate by linking the design features extracted from the design images with CNN and the sensitivity extracted from the customer’s voice. As a result, not only can the evaluation be carried out inexpensively but also the confidentiality is maintained without investigating to the customer. The eval-
valuation of sensitivity in this research is to estimate the ratio of the customer’s voice to the sensitivity category defined in Section 3.6.

We did not use the SD method for gathering customer sensitivity data for three reasons. First, the purpose of this study is to understand customer opinions without bias, so words should not be prepared in advance and presented to respondents. Second, to maintain confidentiality, the target feeling words or images should not be presented to the respondents. The third reason is that it is possible to understand the customer with less bias, with the method of obtaining answers without presenting options to respondents. Indeed, Kardes et al. confirmed that respondents overestimate when presenting choices.\cite{15}

Table 1. Overview of customer sensitivity survey

| Item          | Content                                                                                                                                 |
|---------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Country       | Japan                                                                                                                                 |
| Period        | 3/2017                                                                                                                                 |
| Car           | Extracted the top 75 cars in descending order of number of surveys                                                                 |
| Sample size   | Total: 216196                                                                                                                           |
| Sample        | Target 75 cars: 97492                                                                                                                   |
| extraction    | Random sampling according to population dynamics (age, place of residence) of Japan for those who bought a car at January to December 2016 |
| Survey method | Web survey                                                                                                                              |
| Question      | − Gender, Age, Prefecture, Occupation, Marriage                                                                                         |
|               | − Please answer the manufacturer and car name you bought.                                                                               |
|               | − What kind of charm do you feel about the design of this car? Please fill in freely. (FA)                                               |

3.2 Data used in this research

The customer sensitivity data for exterior designs used in this research were collected by web survey for 216,196 people. These people were sampled at random in accordance with demographic dynamics of Japan from a database of people who bought a car between January and December 2016. As shown in Table 1, the questions covered the demographics of the respondents, the manufacturer and model of the purchased car, and the respondents’ opinions and impressions of the car design.

As shown in Table 2, the target cars are the top 75 vehicles for which we obtained more than 100 records per car. The “Text Freq” column represents the number of data record obtained, so total data records amount to 97,492. The “body type” column represents the shape of the 8 types shown in Figure 3. Here, “Kei” refers to a category of micro car sold primarily in Japan. Kei cars have an engine displacement of 660 cc or less. “Kei_Tall” refers to kei cars that are taller than standard, a subcategory that grown rapidly in popularity in recent years in Japan. Of the 75 cars included, 60 cars are used as learning objects and 15 cars as validation targets for five-fold cross validation of the proposed method. Table 3 shows the target of each validation. To make the targets of each validation a homogeneous group, body types are allocated equally.

Figure 3. Examples of each body type

We prepared 30 images per car for a total of 2,250 design images to be used in the study. The design images are all front 3/4 views showing the front and side of the car. This viewing angle allows the viewer to see the overall design characteristics in a single view, and is commonly used by automobile manufacturers on websites and in catalogs.

3.3 Procedure of this research

As shown in Figure 4, the procedure that the present study followed includes 4 phases. Details of each phase are explained in the following subsections.

Figure 4. Research procedure

3.3.1 Phase 1: Preprocessing design data

Phase 1 involves preprocessing the design data. First, images of the car to be learned are collected for each car. Human
volunteers select 30 images with plain color backgrounds for each car. At that time, it is confirmed that the car in the image is a model that was on sale during the target period between January and December 2016. These images are compressed to 256 × 256 pixels. Using rotations and contrast changes, the number of images is increased ten-fold to 300 images per car.

Table 2. Target cars and volume of customer sensitivity data

| No | Validation 1 | Validation 2 | Validation 3 |
|----|--------------|--------------|--------------|
| 1  | MINI COOPER  | BMW SKIRUES  | Sedan 641    |
| 2  | Honda CRZ    | TOYOTA ALPHARD | Minivan 959 |
| 3  | Nissan DAYS  | ALTO_LAPIN   | Kei 915      |
| 4  | Mitsubishi EKUGN | Toyota AQUA | Compact 5,153|
| 5  | Toyota ESTIMA | Mazda ATENZA | Sedan 198    |
| 6  | Honda INSIGHT| Sedan 301    | Kei 913      |
| 7  | Toyota ISIS  | Sedan 798    | Mazda CX5    |
| 8  | Suzuki JIMNY | Kei 429      | Mazda DEMO   |
| 9  | Honda INWGN_CUSTOM | Subaru FORESTER | SUV 880    |
| 10 | VW POLO      | Compact 523  | Daishu MIRO_COCA |
| 11 | Toyota PORTE | Compact 680  | Daishu MOVE  |
| 12 | Mazda PREMACY | Minivan 1,120 | Kei 2,695 |
| 13 | Suzuki SOLIO | Kei 840      | Mazda ODYSSEY |
| 14 | Subaru STELLA | Kei 597      | Nissan SERENA |
| 15 | Nissan STREAM | Wagon 296    | Toyota SPADE |

Table 3. Assignment of body type in cross validation

| Type | Total | Validation 1 | Validation 2 | Validation 3 | Validation 4 | Validation 5 |
|------|-------|--------------|--------------|--------------|--------------|--------------|
| Compact | 15 | 3 | 3 | 3 | 3 | 3 |
| Kei | 15 | 3 | 3 | 3 | 3 | 3 |
| Kei_Tall | 11 | 3 | 2 | 2 | 2 | 2 |
| Minivan | 14 | 3 | 3 | 3 | 3 | 3 |
| Sedan | 9 | 1 | 2 | 2 | 2 | 2 |
| SUV | 6 | 0 | 2 | 1 | 2 | 1 |
| Wagon | 4 | 1 | 0 | 1 | 1 | 1 |

3.3.2 Phase 2: Extraction of design features

The design data are input into the CNN, and the 60 cars to be learned are categorized according to class and assigned feature similarity scores. The algorithms learned by the CNN during this process are called the feature similarity scoring algorithms. AlexNet, which identified 1,000 classes of cars in ILSVRC 2012, is composed of eight layers.[116] Because there are 60 types of vehicles to be learned per each validation in this study, fewer layers are necessary. As shown in
Figure 5, the feature similarity scoring algorithm, constructed with MXNet, consists of an input layer, three convolutional layers, a fully connected layer, and a softmax layer. In each convolutional layer, introduction of dropout, in addition to convolution or activation, improves generalization performance so as not to overfit. The unit selection probability of dropout is set to $p = .5$, at which level the regularization effect is maximized. The activation function adopts rectified linear units, which have a gradient that propagates without attenuation for positive units and converges quickly. Finally, the similarity scores for the 60 vehicles learned by the softmax layer are output. This phase is carried out 5 times for cross validation.

![Figure 5. Structure of the feature similarity scoring algorithm](image)

**3.3.3 Phase 3: Extraction of design sensitivity**

Phase 3 extracts the sensitivity category for the design of the learning object. The customer opinion obtained by the free answer is processed using by natural language processing and the sensitivity category is input into the design sensitivity database. To achieve this, a sensitivity dictionary is compiled and a semantic understanding algorithm constructed.

**Table 4. Sensitivity categories and word examples**

| Sensitivity category | Word example 1 | Word example 2 | Word example 3 | Sensitivity category | Word example 1 | Word example 2 | Word example 3 |
|----------------------|----------------|----------------|----------------|----------------------|----------------|----------------|----------------|
| D01_Cool             | Cool           | Handsome       | Fearless       | D06_Individual       | Individual     | Unique          | Stimulating    |
| D02_Charming         | Charming       | Cute           | Lovely         | D07_Simple           | Simple         | Monotone        | Basic          |
| D03_Sophistication   | Sophistication | Stylish        | Beautiful      | D09_Masculine        | Masculine      | Wild            | Solidly        |
| D04_Highclass        | Highclass      | Luxury         | Gorgeous       | D09_Family           | Family         | Casual          | Familiarity     |
| D05_Sporty           | Sporty         | Dynamic        | Energetic      | D10_Traditional      | Traditional    | Classic         | Retro          |

First, 97,492 records of text data related to the attractiveness of design obtained by free answer are morphologically analyzed by the open source engine MeCab. The number of emotion categories increases tremendously if words that occur only once or twice are subject to dictionary registration. Therefore, only adjectives or adverbs that occur three or more times are selected, leaving 547 items. Words used to describe products differ depending on the product, and such terms for car exterior design have not been systematized. Therefore, referring to previous research,[6] categories are defined which are considered important for car design. In this case, shape expressions such as “round” or “large”, functional expressions such as “convenience” or “safety”, price expressions such as “expensive” or “cheap”, direct expressions such as...
“good” or “wonderful”, and other irrelevant items are excluded. Also, since the question asked for positive responses, negative expressions are excluded. From among the 547 total items, 169 words describing emotion related to the design are extracted and registered in the dictionary.

The majority of the free answers were single sentences or phrases, and at most two or three sentences. Furthermore, because the descriptions tend to contain duplicate words and phrases, the number of registered words is not very large. As shown in Figure 6, just 33 words account for 80% of the total appearances. The 169 extracted emotion words were arranged into 10 sensitivity categories, as shown in Table 4.

Figure 6. Number of words and cumulative appearance ratio

The semantic understanding algorithm is used to parse the customer opinions. Techniques to understand spoken words can be divided broadly into rule-based methods and statistical methods. Tsuchiya et al. judged emotions according to the rule of 8,024.[17] Harada et al. used statistical semantic matching of, for example, LDA to understand spoken words.[18] Statistical processing is difficult when there are few input words, such as with our free answers. In addition, we are focused on expressions that describe designs, so we do not need a large database. Therefore, we adopt the rule-based approach.

We constructed four rule functions for the semantic understanding algorithm, as shown in Table 5 along with examples.

Table 5. Examples of semantic understanding result

| No | Algorithm         | Example                                                                 | Target car   | Sensitivity category | Score |
|----|-------------------|-------------------------------------------------------------------------|--------------|----------------------|-------|
| 1  | Dependency        | It is not stylish, but I feel familiarity.                               | GOLF         | D03_Sophistication    | 0     |
|    |                   |                                                                         | D09_Family   |                      |       |
| 2  | Multiple negation | The surroundings say that the Prius is not cool, but I can not agree at all. | PRIUS        | D01_Cool             | 1     |
| 3  | Affirmative doubt | Which is a luxury car, Toyota Alphard or Benz Viano? Is it alphard?     | ALPHARD      | D04_Highclass        | 1     |
| 4  | Comparison        | Mercedes’ C-class is cooler than the BMW 3 Series at all.               | 3 SERIES     | D01_Cool             | 0     |

The first function, “dependency”, is focused on the affirmation or negation of the term stored in the dictionary, and when a term is negated, no score is given. For example, “stylish” and “familiarity” are detected. Because “stylish” appears with “not” it is negated no score is given. In contrast, “familiarity” is given a score.

In the second function, “multiple negation”, when multiple negative words are detected, if it is judged positive overall, a score is given. Sixty-five negative words were detected, including “disgusting”, “disappointed”, “bad”, and “terrible”. For example, the term “cool” is negated twice; this is judged to be positive, so a score is given.

The third function, “affirmative doubt”, gives scores to question sentences that are seeking confirmation. Four words are registered. For example, a score is given for “luxury” because the question is asking for agreement that the target
car (ALPHARD) is a luxury model.

The fourth function, “comparison”, understands the dependency around comparison words, and does not give a score in the context where another car or an older model prevails. For example, no score is given for “cool” because a different car (C-class) is noted as cooler than the target car (3 SERIES).

Natural language processing consisting of the above dictionary, morphological analysis, syntax analysis, and rules is called semantic understanding algorithm which is implemented in Python. The composition ratio of the sensitivity categories accumulated for each car for each sensitivity category by this algorithm is called the sensitivity database. Table 6 shows examples of four cars. By car, we can see that the distribution of sensitivity voices changes greatly.

Table 6. Examples from the design sensitivity database

| Sensitivity category | JUKE   | MIRA_COCOA | VELLFIRE | VOXY   |
|----------------------|--------|-------------|----------|--------|
|                      | Freq   | Rate (%)    | Freq     | Rate (%) | Freq   | Rate (%) | Freq     | Rate (%) |
| D01_Cool            | 22     | 18.33%      | 2        | 0.53%    | 69     | 33.66%    | 127      | 64.47%   |
| D02_Charming        | 23     | 19.17%      | 327      | 87.20%   | 6      | 2.93%     | 14       | 7.11%    |
| D03_Sophistication  | 8      | 6.67%       | 16       | 4.27%    | 4      | 1.95%     | 0        | 0.00%    |
| D04_Highclass       | 4      | 3.33%       | 2        | 0.53%    | 103    | 50.24%    | 8        | 4.06%    |
| D05_Sporty          | 2      | 1.67%       | 0        | 0.00%    | 3      | 1.46%     | 6        | 3.05%    |
| D06_Individual      | 53     | 44.17%      | 8        | 2.13%    | 12     | 5.85%     | 9        | 4.57%    |
| D07_Simple          | 1      | 0.83%       | 12       | 3.20%    | 1      | 0.49%     | 6        | 3.05%    |
| D08_Masculine       | 7      | 5.83%       | 1        | 0.27%    | 6      | 2.93%     | 10       | 5.08%    |
| D09_Family          | 0      | 0.00%       | 0        | 0.00%    | 1      | 0.49%     | 17       | 8.63%    |
| D10_Traditional     | 0      | 0.00%       | 7        | 1.87%    | 0      | 0.00%     | 0        | 0.00%    |
| Total               | 120    | 100.00%     | 375      | 100.00%  | 205    | 100.00%   | 197      | 100.00%  |

Because the semantic understanding algorithm in Phase 3 was commonly used for each cross validation, implementation was done only once. The results of the semantic understanding algorithm were input into the database and extracted for each validation.

3.3.4 Phase 4: Evaluation and validation of design sensitivity

In Phase 4, the composition ratio of the sensitivity category of the vehicles to be validated are estimated and the accuracy is validated. An estimated value of the customer sensitivity of the validation target car is calculated from the similarity score obtained in Phase 2 and the sensitivity database obtained in Phase 3.

The design scoring algorithm is shown in equation (1):

$$\text{Score}_{i,j} = \frac{\sum_{k=1}^{60} (w_{i,k} \times \text{Score}_{e,k,j})}{\sum_{j=1}^{10} \text{Score}_{e,i,j}}$$

(1)

where, $i$ is the target car to be validated, $j$ is the sensitivity category, $k$ is the target car to be learned, and $w$ is the similarity score. The sensitivity estimated by the above formula is compared with the customer sensitivity, and its accuracy is evaluated by mean absolute percentage error (MAPE).

4. RESULTS AND DISCUSSION

4.1 Algorithm accuracy

In this study, the feature similarity scoring algorithm for extracting design features (Phase 2) and the semantic understanding algorithm for customer design sensitivity (Phase 3) are centralized. We carried out accuracy validation for both algorithms.

As shown in Figure 7, all five repetitions of the validation of Phase 2 converge at about 95% accuracy. Although the learning data included 60 models, the accuracy of 95% was achieved after only 30 models were used as learning data. As shown in Table 7, we confirmed an accuracy level of over 93% in all models. Thus, we confirmed the accuracy of the feature similarity scoring algorithm.

Table 7. Validation accuracy of the convolutional neural network

| Validation | Validation | Validation | Validation | Validation |
|------------|------------|------------|------------|------------|
| 1          | 2          | 3          | 4          | 5          |
| Correct    | 59         | 59         | 57         | 56         | 58         |
| Miss       | 1          | 1          | 3          | 4          | 2          |
| Correct Rate | 98.33%   | 98.33%   | 95.00%   | 93.33%   | 96.67%   |

The semantic understanding algorithm was validated using the indicators of precision and recall. Both of these indicators were verified with data of 10 records in each sensitivity category.
category, 100 records in total. As shown in Table 8, we con-

firmed a precision accuracy of 86.00% and a recall accuracy

of 94.00%. The process of extracting customer sensitivity by

the semantic understanding algorithm was conducted only once, regardless of cross validation; therefore, Precision and

Recall were also validated only once.

Figure 7. Accuracy rate of convolutional neural network learning

Table 8. Precision and recall

| Sensitivity category | Precision | Recall |
|----------------------|-----------|--------|
|                      | Total     | Correct| Total     | Correct|
| D01_Cool             | 10        | 10     | 10        | 10     |
| D02_Charming         | 10        | 10     | 10        | 8      |
| D03_Sophistication   | 10        | 9      | 10        | 9      |
| D04_Highclass        | 10        | 8      | 10        | 10     |
| D05_Sporty           | 10        | 8      | 10        | 10     |
| D06_Individual       | 10        | 7      | 10        | 10     |
| D07_Simple           | 10        | 8      | 10        | 9      |
| D08_Masculine        | 10        | 9      | 10        | 8      |
| D09_Family           | 10        | 9      | 10        | 10     |
| D10_Traditional      | 10        | 8      | 10        | 10     |
| Total                | 100       | 86     | 100       | 94     |

Example sentences that failed semantic comprehension are

shown in Table 9. There are two examples of where the pre-

cision declined. In the first example, the text “feel the status”

is not related to design. In the second example, “rare” is not

referring to the car but to the respondent, giving a false posi-

tive score. There are also two examples in which the recall

rate decreased. In the first example, “lovely” is negated by

“although” so no score is given. However, “although” is not

necessarily negative and this should have received a score.

In the second example, “too cute” is excessive, considered as

a negation and not given a score, but it does have a positive

meaning. To correct such failures, it is necessary to continue

improving dictionaries and rules while taking side effects

into account.

Table 9. Example sentences that failed semantic

comprehension

| Indicator | Text | Sensitivity category | Score |
|-----------|------|----------------------|-------|
| Precision | I feel the status on the ride. | D04_Highclass | 1 |
|           | It’s rare for me that I thought it cute. | D06_Individual | 1 |
| Recall    | Although it is lovely looking from far, there is a heavy feeling when looking at nearby. | D02_Charming | 0 |
|           | The exterior is too cute! | D02_Charming | 0 |

4.2 Sensitivity estimation and accuracy validation

We evaluated the difference between the composition ra-

tio (estimated value) of the sensitivity category obtained by

equation (1) shown in Phase 4 and the composition ratio

(estimated value) of the customer sensitivity category shown

in Phase 3. In the example shown in Table 10, the MAPE of

the Mini Cooper is 4.87%. This verification was conducted

with five-fold cross validations.

Table 11 shows the MAPE for each sensitivity category ob-

tained by cross validation, and the overall MAPE for each of

the 10 categories. The mean MAPE among all categories is

5.26%. Evaluations for all sensitivity categories are within

10%. The MAPE for the ‘Charming’ category is 9.39%,
which is the most inaccurate. The sensitivity ‘Charming’ is thought to be difficult to estimate because it has various shapes such as round, square and small. The largest difference between the maximum value and the minimum value is 4.20%, for the ‘High class’ category. The reason for this is that ‘High class’ is not specific to a particular car body type.

Table 10. An example of mean absolute percentage error for the Mini Cooper

| D01  | D02  | D03  | D04  | D05  | D06  | D07  | D08  | D09  | D10  | Total |
|------|------|------|------|------|------|------|------|------|------|-------|
| Cool | Charming | Sophistication | Highclass | Sporty | Individual | Simple | Masculine | Family | Traditional |
| True value  | 27.90% | 17.36% | 9.81% | 16.47% | 6.50% | 9.70% | 6.02% | 3.48% | 2.06% | 0.68% |
| Estimated value | 27.59% | 24.14% | 0.00% | 10.34% | 10.34% | 17.24% | 0.00% | 6.90% | 0.00% | 3.45% |
| MAPE | 0.32% | 6.77% | 9.81% | 6.13% | 3.85% | 7.54% | 6.02% | 3.41% | 2.06% | 2.77% |

Table 11. Mean absolute percentage error by each sensitivity category obtained by five-fold cross validation

| Validation | D01  | D02  | D03  | D04  | D05  | Average |
|------------|------|------|------|------|------|---------|
|            | Cool | Charming | Sophistication | Highclass | Sporty |         |
| 1          | 8.70% | 10.98% | 6.07% | 9.24% | 5.89% | 9.05%   |
| 2          | 7.36% | 8.96% | 4.64% | 7.59% | 3.16% | 5.91%   |
| 3          | 9.88% | 10.21% | 2.94% | 11.44% | 3.84% | 8.18%   |
| 4          | 8.18% | 8.14% | 3.31% | 8.07% | 2.11% | 8.11%   |
| 5          | 11.11% | 8.65% | 4.32% | 7.24% | 2.59% | 9.88%   |
| Average    | 9.05% | 9.39% | 4.26% | 8.72% | 3.52% | 5.33%   |
| max - min  | 3.74% | 3.28% | 3.13% | 4.20% | 3.77% | 5.26%   |

Because the number of records varies as shown in Table 3, MAPE for each body type shows the results on total average instead of every cross validation. As shown in Figure 8, the body type with the largest MAPE is Sedan’s 6.62%, then 5.90% for Minivan. This factor is thought to be attributed to brand image, which does not appear only in exterior design. For example, VELLFIRE and VOXY shown in Table 6 are made by the same company (Toyota) and their shapes are similar, but the customer’s sensitivity is concentrated on high-class for the former and cool for the latter. As in the example, even though the exterior designs are similar, Sedans and Minivans tend to be split into Cool and High-class depending on the brand image.

Figure 8. Mean absolute percentage error for each body type

In the present study we considered 10 sensitivity categories; however, additional categories can be evaluated using the proposed method and algorithms. Although not limited to this method, a weak point of machine learning is that it cannot adapt to tendencies that have not been learned. In this research, we used designs of existing vehicles as learning data. However, parts are becoming modularized and new companies are developing electric vehicles. Therefore, it...
is difficult to evaluate designs using only past trends of the automobile industry. Manufacturers should collect customer sensitivity data to innovative designs and develop original sensitivity evaluation algorithms.

5. Conclusion

In this research, we proposed a technique to quantitatively evaluate design sensitivity by linking design features extracted from the design images and the sensitivity extracted from the customer’s voice. The evaluation of sensitivity in this research is to estimate the ratio of the customer’s voice to 10 sensitivity categories was 5.26% MAPE as a result of five-fold cross validation.

This method has three merits. Firstly, it is to estimate sensitivity without disclosing designs which are confidential for the companies. Secondly, it is unnecessary for humans to define design features which is a huge amount work, and it is also possible to evaluate a design as an integrated body rather than elements. As the designs should be evaluated as a comprehensive body, it is not certain whether the perception of the customer is fully grasped regardless of how humans precisely define the features. Thirdly, it can be used affordably at the design site. In recent years, in order to ensure confidentiality and to evaluate design as a comprehensive body, neuroscience attracts attention. However, neuroscience approach not only requires dedicated machines but also has a heavy burden on the examinee, so the cost burden is large.

In recent years, the competitive domain of the manufacturing industry has shifted from functional value to emotional value. Among the emotional value design is the interface closest to the customer, but for companies it is often difficult to evaluate design from the viewpoint of confidentiality. We hope this research will contribute to trial and error at the design site. In future studies, we intend to extract features of brands image from promotional images.

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