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A fuzzy rule induction method using genetic algorithm

Toshio Tsuchiya *, Tatsushi Maeda, Yukihiro Matsubara, Mitsuo Nagamachi

Faculty of Engineering, Hiroshima University, 1-4-1, Kagamiyama, Higashi-Hiroshima 739, Japan

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Abstract

Kansei engineering expert systems simulate human perception for the evaluation of product design. A procedure of inducing a fuzzy decision tree for the Kansei engineering system is described for the analysis of driving comfort of automobiles. A method is proposed in this study for inducing the tree based on a genetic algorithm. Linguistic fuzzy rules are acquired by tracing the generated tree from the root node to leaf ones. The results are compared with the model of quantification theory type I which is one of the conventional statistical methods.

Relevance to industry

In recent years, human-centered product design has become an important matter for manufacturing. Kansei engineering supports the design of satisfactory products in a psychophysical perspective.

Keywords: Kansei engineering; Fuzzy decision tree; Genetic algorithm; Knowledge acquisition; Driving comfort

1. Introduction

Nowadays, products are generally conceived as complying with high standards of quality, and the consumer's purchasing criteria change more to preference-related characteristics as he or she is accustomed to enjoy high quality products. That is, when consumers purchase a product, their preference is influenced by design quality as well as by functionality. Thus, if the design of a product meets the specific needs and feelings of consumers, it will be more likely to be purchased. Consumer's needs and feelings are also useful for manufacturers, for example, if a consumer wants to buy a kitchen, it would be more beneficial for him or her to see photographs or computer graphics of the models which match to his or her image.

The Japanese word, *Kansei*, has a meaning of 'feeling', 'impression' and/or 'emotion'. Kansei engineering is a method for translating a consumer's image or feeling into real design components (Nagamachi, 1991, 1995), and Kansei engineering expert systems (KES) are the computer systems that support consulting sales or product design. Kansei engineering, as an ergonomic consumer-oriented technology, enables a consumer's image or feeling to be incorporated in the design process of a new product. In relation to KES, much research has been pursued in the field of automobile, clothing, house interior design, to name a few. Most research has been done to investigate the relationship between

* E-mail: tsuchiya@mng.sys.hiroshima-u.ac.jp, Tel.: +81 824 24-7860, Fax: +81 824 22-2261.

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interior design of cars and human perception. Here, consumers' perception is strongly affected by the interior design and interior dimensions, due to their influence on driving comfort. Therefore, it is of great importance to investigate how the physical constraints created by the interior dimensions of a car are related to human perception. The main purpose of this study was to construct a KES for the design of automobile interior space. This paper illustrates a new approach to constructing the knowledge base of the KES.

Statistical analyses play an important role in the KES. Hayashi's quantification theory type I (Hayashi, 1976) has been used as the most useful statistical tool in the KES. The linear regression model of quantification theory type I provides good relational data to derive a relationship between human perception and product design factors. However, the model has several shortcomings. It assumes that all predictors are linearly related to each other. Yet, in many cases, the combination of different design factors yields a distinct perception of the design. When explanatory variables correspond to each design factor and a dependent variable corresponds to quantitative measures of human perception, there is usually an interaction or dependency between design factors. It is rarely possible to consider these interactions with the model. For example, one usually does not wear a neck tie with a collarless shirt. The model cannot solve the dependency between these attributes. In other words, the model does not suffice to describe the whole design effectiveness composed of many design factors, although it fairly estimates the amount of influence of a single attribute.

Another difficulty is that there are too many factors to design a product. The model has a statistical constraint about the number of explanation variables. If we wish to analyze concurrently the effect of numerous design aspects, we must increase the number of evaluation samples related to the product design. In reality, however, the number of design alternatives for evaluation is constrained by the limited time and budget. A means to solving this problem is to choose carefully the most influential design factors. However, this is also a difficult concept to apply when the design item to be evaluated becomes too expensive or large in size such as vehicle interior space.

To solve these problems, a method is proposed in this study to acquire the knowledge for the KES in the cases that have many design attributes. In our method, Kansei reasoning rules are represented by a fuzzy decision tree from which linguistic fuzzy rules are extracted (Weber, 1992a,b). The fuzzy decision tree offers an opportunity to describe the structure of important design factors in terms of KES rules and shows the influence of those factors on human Kansei. The linguistic fuzzy rules that represent the relationship between design items and human Kansei are extracted from the trees generated. We also propose a method to induce fuzzy decision trees using a genetic algorithm (GA) (Goldberg, 1989). GA is a technology for search, optimization or machine learning based on the mechanics of natural selection and natural genetics. The natural selection process of the GA extracts the useful design items from a multitude of design attributes. Through the process, we attempt to create an optimal tree for representing human Kansei. The method is capable of solving the difficulty in treating numerous independent variables concurrently in a very short computation time.

Our approach has specifically focused on the analysis of human comfort. An experiment was based on the questionnaires on 20 vehicles completed by the designers of an automobile company. The influence of interior dimensions on human comfort was analyzed using the experimental results by employing the fuzzy decision tree with GA. The linguistic fuzzy rules induced are then evaluated. Also, the efficiency of the proposed method was confirmed by a comparison with the application of conventional methodology.

2. Kansei engineering expert system

Kansei engineering expert systems are computer systems that employ Kansei engineering for analyzing human Kansei. The architecture of the system is shown in Fig. 1. The system is composed of three basic modules: adjective processing module, inference engine, and graphic module. The system has two types of reasoning processes: Kansei reasoning and Design reasoning. The former process, also called *Forward* (Nagamachi, 1994), infers the design specifications from human Kansei, whereas the latter process, also called *Backward*, infers the human Kansei represented by adjective words from the design elements. The information of human Kansei is stored in the image database which consists of the results of the statistical analysis according to the customer characteristics such as age and gender.

The procedure of the forward reasoning is as follows: A user enters into the system one or more adjective words representing his or her Kansei or, simply, the user requirement. Here, all adjectives used to describe a product can be considered as Kansei words. The adjective processing module searches the adjective database to translate user-inputted adjectives into the basic adjectives that were collected in advance from magazines and shops and were stored in the database. The reasoning module then analyzes the relationship between translated words and human image from the image database, and infers a design arrangement. At the same time, it refers to the knowledge base to check if conflicts exist between design items. The graphic module processes the inferred design using the graphic database. Kansei engineering systems are designed for the following functions:
1. communication between designer and customer,
2. customer support for the selection of products,
3. designer support for the evaluation of Kansei design.

In this paper, our purpose is to analyze the relationship between the interior dimensions of automobiles and human comfort (especially concerning the feeling of 'openness' and 'oppression'). In general, the interior dimensions are defined by the vertical, horizontal and angular dimensions measured with respect to the reference eye point and the seating reference point (SgRP), as shown in Fig. 2. The features of automobiles concerning comfort can then be defined by a combination of such dimensions. Considering physical constraints of the interior space, it is important in many cases for the designers to optimize the dimensions defined above in a psychophysical sense. The computerized KES aims at guiding the designer to check the appropriateness of his or her design alternatives in terms of interior dimensions.

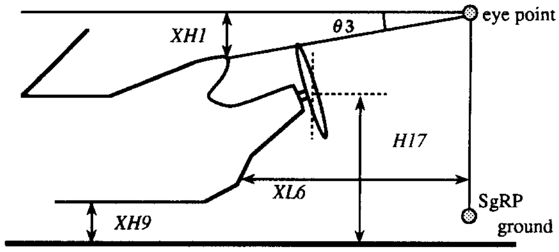


Fig. 2. Example of the interior dimensions of a vehicle.

3. Fuzzy reasoning rules

In constructing a Kansei engineering system, the knowledge acquisition for the image database of

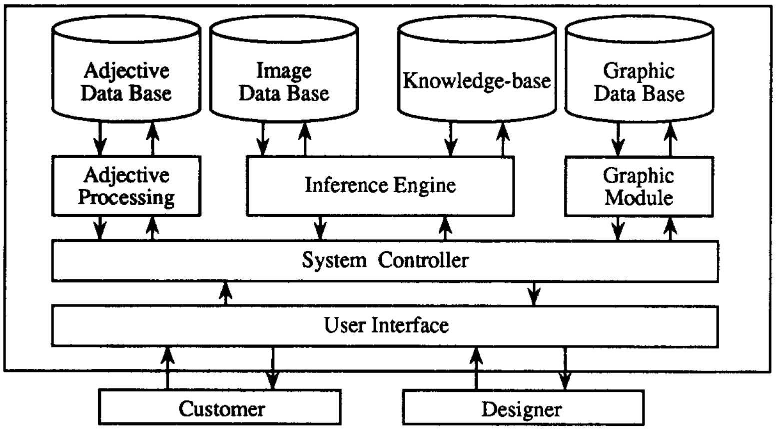


Fig. 1. The architecture of Kansei Engineering Systems (KES).

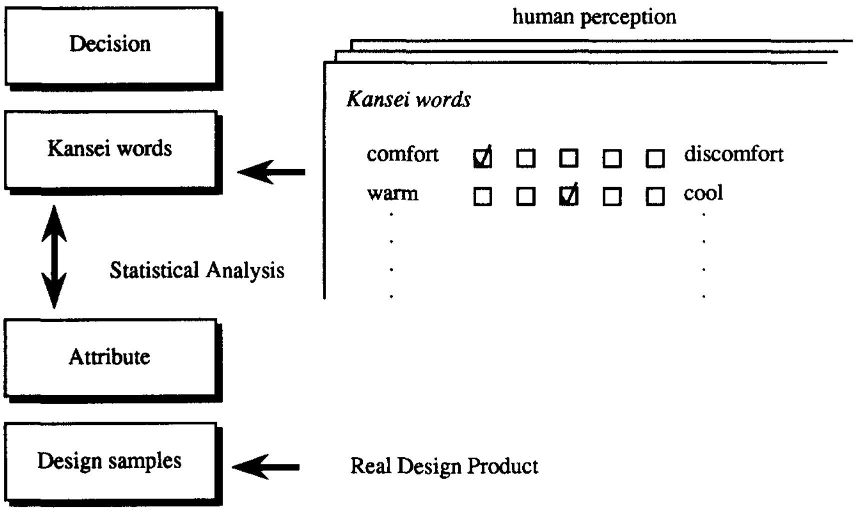


Fig. 3. The questionnaire used in the *Kansei* evaluation experiments and its analysis.

Kansei reasoning and design reasoning is based on the experiments using actual design samples, e.g., cars, clothing etc. In the experiment, subjects were asked to test various design samples and to evaluate them with the questionnaires based on the Semantic-differential technique (Osgood et al., 1957). The results were then statistically analyzed. In practice, the fundamental Kansei words are extracted by a factor analysis from the massive set of general Kansei words. Then, each Kansei word is analyzed using quantification theory type I. In the statistical analysis, the actual design factors are a set of dependent variables and the Semantic-differential data are used as independent variables, as depicted in Fig. 3. The statistical analysis focuses on the relationship between product design and human perception, operationalized by Kansei words. The results are stored in the image database.

As mentioned, however, the analysis of quantification theory type I has two major difficulties: the number of design items and their independence. Although the number of design samples to be evaluated in the experiment must be increased in order to consider a large number of design aspects, it would

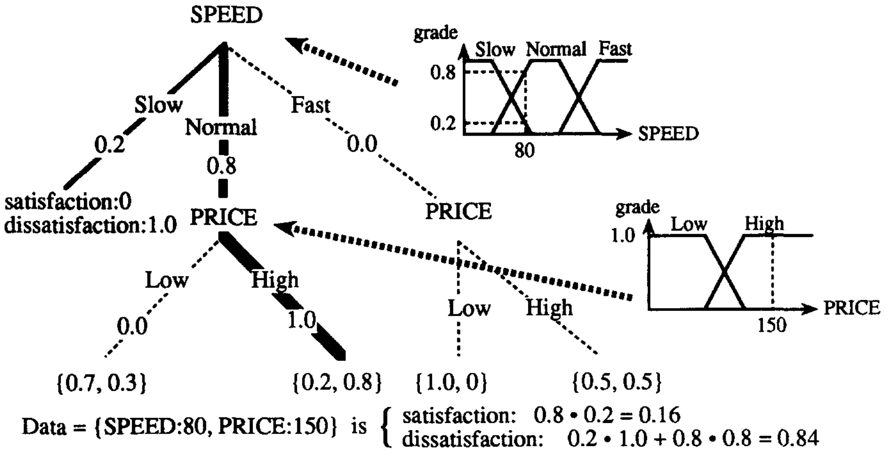


Fig. 4. An example of fuzzy decision tree for classifying cars into satisfaction or dissatisfaction.

be rarely possible to use enough design samples. Therefore, the number of design dimensions has to be limited. It is, however, very difficult to extract a set of effective variables from a large number of designs. Also, the model is unable to represent the dependence between design dimensions, since human perceptions to the combined effects of various design items are very complex and ambiguous.

To solve these problems we employed the rule-based reasoning represented by fuzzy decision trees. Fuzzy reasoning is a useful tool for the features that are ambiguously related to a human feeling concerning the product design. Furthermore, the fuzzy decision tree can represent the generalized rules that have a structure similar to complex human Kansei. We can therefore generate effective linguistic fuzzy rules in a tree style.

As shown in Fig. 4, the fuzzy decision tree consists of fuzzy linguistic rules with nodes and membership functions. A node has the attributes of the specific design samples and the fuzzy sets represented by membership functions. The membership functions are ambiguously classified values according to the attributes of the nodes. Human perception or feeling essentially includes many ambiguous factors. The fuzzy reasoning is an effective means for the representation of such ambiguous human Kansei. Especially in analyzing the perceived comfort of automobile interior space, the procedure is capable of computing ambiguous measures estimated by humans. The tree classifies the samples according to their attributes. Here, the attribute and the class correspond to the design aspects and Kansei, respectively. The reasoning based on a tree structure is an appropriate representation of the complex human reasoning process, which includes interactions between attributes. A user of the system can easily get the information about complex human Kansei via linguistic representation.

Fig. 4 shows an example of using the fuzzy decision tree. In the example, the relationship between attributes {SPEED, PRICE} of the design samples of passenger cars and the corresponding evaluation by the customer {satisfaction, dissatisfaction} is illustrated. To begin with, a sample automobile is classified according to the attribute, SPEED, at the root node. Here, the membership value, 80, of the attribute SPEED (SPEED: 80) is conceived as slow (0.2) to normal (0.8) corresponding to its membership function. Then, the design samples labeled 'slow' to 'normal' are sent down to the lower level node where the membership function of the attribute, PRICE, is then calculated. At the same time, the membership values of the design samples are multiplied by the upper level ones. Finally, when the lowest level is reached, the partial result of each classification is obtained by multiplying the grade of traced nodes and the membership value of the leaf level. The total result is calculated by a summation of partial results. In addition, their overall satisfaction with a specific design sample, and their corresponding purchase decision is registered. In our example, the fuzzy decision tree classifies the car with {SPEED: 80, PRICE: 150} into {satisfaction: 0.16, dissatisfaction: 0.84}.The tree contains five fuzzy production rules, e.g.,

> if SPEED is Normal and PRICE is Low
> then decision is {satisfaction: 0.7, dissatisfaction: 0.3}

4. Knowledge acquisition method

ID3 or its variants is well known as a method for inducing a decision tree. ID3 which introduces the concept of information content is a very efficient approach and allows for the induction of the compact tree in a short computation time. However, its descriptive power is not enough to extract linguistic fuzzy rules, despite its short computation time. Since our purpose is to describe the relationship between human Kansei and product design and to extract the linguistic rules for Kansei forward and backward reasoning, the extracted rules should be capable of describing the human reasoning process. In other words, the structure of a generated tree should be able to represent human perception, or to represent what or how design dimensions influence human Kansei. A new method is therefore proposed in this study to induce linguistic rules via a fuzzy decision tree based on a genetic algorithm (FDTGA). The specific characteristic of GA is that the structure of the tree, which is a representation of the human evaluation process, is described by chromosomes. Specifically, the framework of a classifier system of

GA is introduced to induce the tree. The method includes the principle of a structure learning process defined as generating a compact and structured tree which has a human evaluation structure (Tsuchiya et al., 1994).

The coding of a chromosome is defined in Fig. 5. A chromosome corresponds to a node which has classification rules and selection rules. The classification rules classify a sample with attributes according to membership functions. The number of membership functions is the same as the number of design aspects. When a sample is classified by the classifier rule, its membership value, x, is calculated by using its attribute value, corresponding to the rule's attribute and membership function. The sample is labeled by the membership value and goes to the next level node indicated by the labeled membership function. On the other hand, the selection rule determines the rule of the next level node to indicate the labeled membership function. The selection rules described by the classifier have the information of the link which is the address and the pointers to the lower level node. The rule of the lower level node is derived by matching the label and pointer. As shown in Fig. 5, the rule under the design category, A_1, of a design item, x, has the label {101}. A chromosome also has the fitness value which represents its accuracy. The fitness value implies the degree of contribution to the tree performance. The higher the fitness value of a chromosome, the higher its priority to compete with other chromosomes. An illustration of the chromosome defined in Fig. 5 has three membership functions in the classification rule. It means that this node has three lower level nodes with three pointers. The decision tree is constructed by classify-

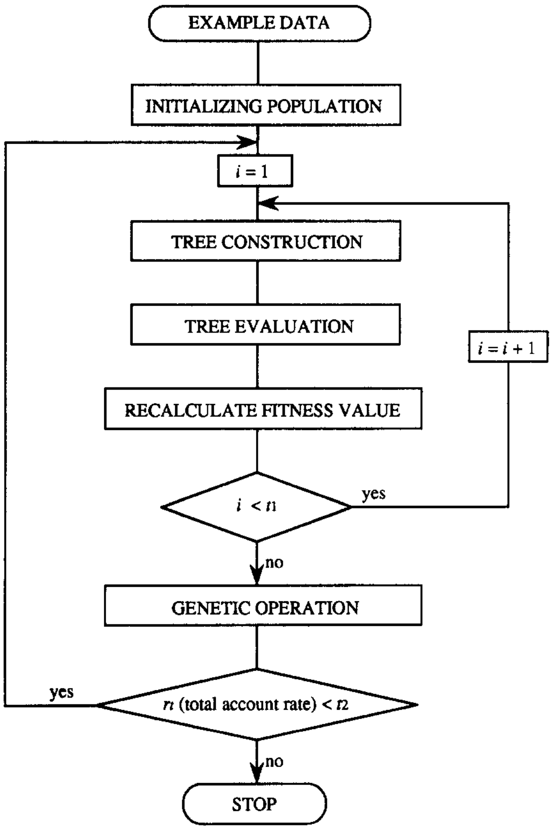


Fig. 6. The process of tree induction using genetic algorithm.

ing the given set of samples. The number of membership functions decide the number of lower level nodes and the bit pattern of classifier decides the rule of lower level nodes. If the rule at the root node is given, the tree structure is constructed automatically. The tree construction algorithm decodes the chromo-

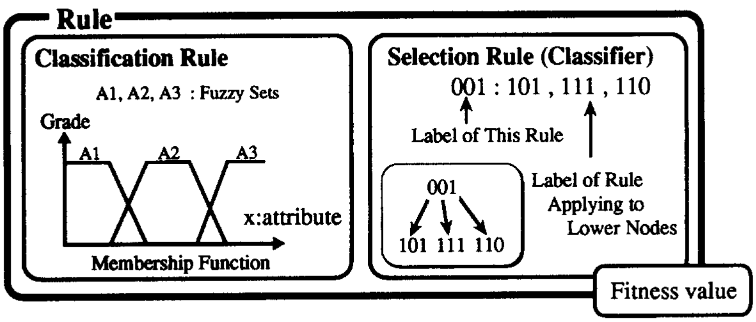


Fig. 5. Coding of the chromosome with classification rule, selection rule and fitness value.

Table 1
Extracted factors from factor analysis about Kansei words of real vehicles

Factors	Significant Kansei words
Factor 1	openness, relaxedly
Factor 2	speedily, young
Factor 3	colorful, womanish
Factor 4	simple, lightly
Factor 5	tight, narrow, oppressive

some with classified samples. The process is as follows;

STEP 1: Choose a chromosome as the root node which has the largest fitness value.

STEP 2: Classify the sets of the samples with the attributes to the lower level node according to the classification rules.
Calculate the grade of each membership function, a_i, where i is the lower level node.

STEP 3: Choose the chromosomes which corre - spond to the lower level nodes with the pointers to the root node, address of the other node and the fitness value.

STEP 4: Calculate the account rate, r_{ij}, of each lower level node:

$$r_{ij} = a_{ij}/S_k\ a_{ik},$$

where i and j are the node and its class, respectively.

Table 2
Fitness value of the interior dimensions calculated by proposed method

Dimensions	Fitness value
H122	2293
XL58	2292
H61	2291
XL70	2193
XH17	520
XH46	247
XL7	138
XH43	53
Q51	49
XW7	38

If $\max_j(r_{ij}) > e$ (e is the threshold of minimum account rate), then stop the growth of the lower level node and it becomes leaf labeled account of class, else go to STEP 2 for unlabeled nodes.

The induction method based on GA for the defined tree is shown in Fig. 6. First, an initial population, which is a set of rules, is generated for each attribute. After constructing the decision tree by using the generated population, the fitness values of chromosomes are updated using a Bucket Brigade Algorithm (Booker et al., 1989). Each fitness value of a rule is renovated for constructing trees. If the account rate of a leaf node is high, then it gets the positive reward according to its accuracy. The degree

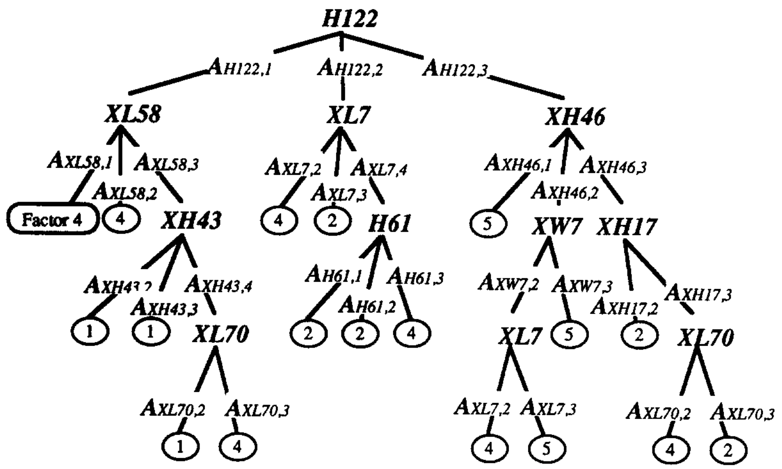
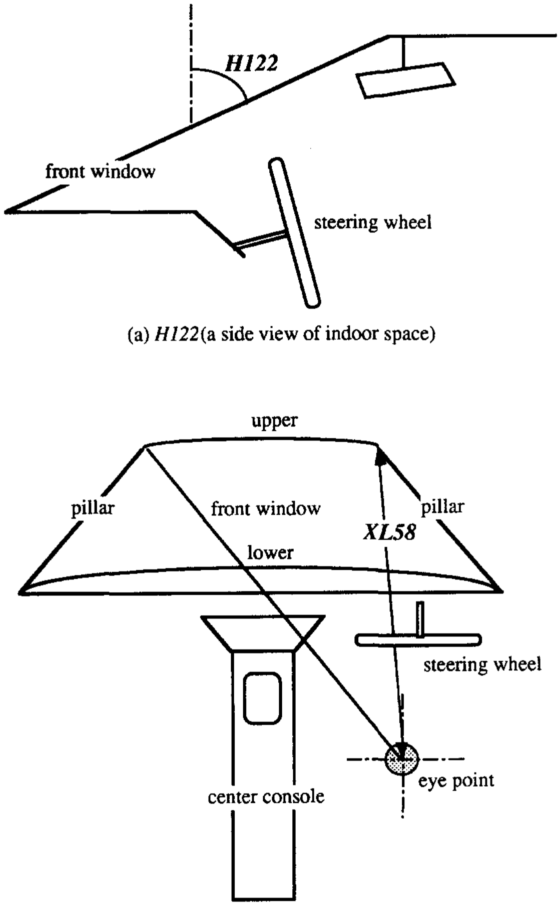


Fig. 7. The optimal decision tree induced by proposed method.

of reward is also related to the number of classified samples, because a node which classifies the large number of samples should be increased by its rewards. A part of the acquired reward is transmitted to the upper level node. The higher the account rate on the lower level nodes, the more it gets the positive reward. The acquired reward renews the fitness value of the adopted rules. A high fitness value has a higher possibility the next time a tree is constructed. Thus, the rule which has the highest fitness value is selected on the root node. In contrast, the lower fitness values are weeded out by genetic reproduction which has selection, crossover and mutation procedures. The procedure generates the new rules and dismisses the lower fitness rules. The reproduction also changes the bit pattern of the classification rules and generates the new structure of the tree.

When the fitness values are updated repeatedly all chromosomes can be reproduced by GA. The procedures to construct the decision tree and to reproduce classifiers make the chromosomes preserve the important rules and links. A chromosome shows a partial structure, centered by its own position. The decision tree which is generated by linking the chromosomes with high fitness values 'subconsciously' has the structure which is enclosed in the sample data. In other words, if a part of the structure is broken by genetic operation, another part of the structure which has already been learned takes the place of the broken part. Thus, the total structure is never lost. On the other hand, if an effective structure is generated, then it is recomposed without breaking the already learned structure. Therefore, the proposed methodology can efficiently induce the tree structure. Unlike conventional statistical methods, it is not necessary to select the variables in advance, because it has the procedure to control the growth of a tree by genetic operation. The procedure to give the reward according to the number of classified samples is able to control the tree growth with genetic reproduction.



(a) *H122*(a side view of indoor space)

(b) *XL58*(a down view of indoor space)

Fig. 8. Interior dimensions (*H122* and *XL58*).

5. Experimental results

The tree induction algorithm was applied to an example of analyzing vehicle comfort. The evaluations of driving comfort estimated by using the semantic-differential scale were used as input data. In the experiment, 41 designers of an automobile company evaluated 60 dimensions of 20 vehicles with 100 Kansei words. These data were analyzed by using a factor analysis with a set of Kansei words and evaluation items. Five factors which represented the perception of automobile comfort were extracted as listed in Table 1. The total variance explained by the five factors was 55.9%. The coordinate values of each sample vehicle were calculated for the components explained by the variances explained. The membership value of each sample on these factors was derived by these values. The fuzzy decision tree was induced using the sample data. The membership functions of 62 dimensions were set with reference to the designers' opinion. We induced the decision trees that classified the sample vehicles to the five factors according to the dimensions. Fig. 7 shows the optimal solution of the decision tree. Each node shows the attribute, while each leaf shows the factor. The tree contains 18 linguistic fuzzy rules such as the one described below.

if $H122 = A_{H122,3}$ and $XH46 = A_{XH46,1}$,
then the car belongs to Factor 5, meaning discomfort.

The proposed method accurately induced the tree. Table 2 shows the fitness values of the rules which represent the degree of influence. From the structure of the induced tree and the fitness values of the rules, it seems that the interior dimensions H122 and XL58 have much influence on driving comfort, as shown in Fig. 8. For example, when H122 is big and XL58 is small, then a driver feels comfortable, which indicates that the typical comfort space is characterized by the vertical angle of the front window and the distance from the eye point to the right front pillar.

Fig. 9 shows the second optimal solution. This is constructed by the replacement of H122 with XL58 at the root, since XL58 had the second maximum fitness value. Such a replacement demonstrates that the acquired rules can derive many substitutes of the structure stored in the rules in order to induce the structure of human Kansei.

Table 3
The upper 20 partial correlation coefficients of dimensions from quantification type I

Dimensions	Openness	Oppression	Relaxed	Tight
H122	0.959	0.897	0.818	0.918
H61	0.950	0.724	0.936	0.939
Q45	0.843	0.859	0.602	0.854
XL68	0.841	0.774	0.362	0.426
XL58	0.834	0.930	0.783	0.886
XL8	0.828	0.926	0.740	0.924
XL83	0.827	0.884	0.621	0.714
XL60	0.818	0.927	0.761	0.885
W20	0.813	0.896	0.950	0.919
W5	0.812	0.507	0.845	0.654
LBA	0.808	0.720	0.852	0.709
XW41	0.796	0.754	0.844	0.766
Q15	0.783	0.630	0.812	0.678
Q52	0.775	0.689	0.611	0.690
XL7	0.774	0.431	0.694	0.840
XL61	0.768	0.700	0.531	0.801
XH17	0.762	0.821	0.820	0.845
XH	0.758	0.640	0.790	0.762
Q51	0.752	0.604	0.748	0.607
W32	0.750	0.864	0.942	0.888

Next, a comparison is made with the conventional statistical analysis. The partial correlation coefficients of the dimensions calculated by using the quantification theory type I are shown in Table 3. A partial correlation coefficient refers to the relation to human Kansei. We analyzed repeatededly with three to four randomly selected dimensions from a sample

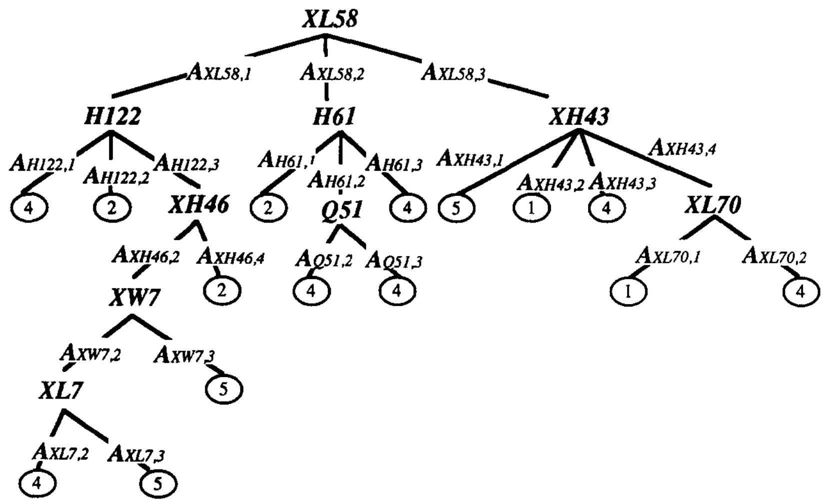


Fig. 9. The next optimal solution with construction of dimension *XL58* on the root node.

of 62 dimensions. The order of coefficients, which indicate the importance of the dimensions, was almost the same as that of the fitness values produced by our method. These coefficients were also roughly the same as the fitness values of GA. This demonstrates that our method has the ability to acquire the effective values from a large number of dimensions because the greater coefficient dimensions also show the greater fitness values.

6. Conclusion

The main purpose of the research was to construct the knowledge represented in the form of a fuzzy decision tree for the Kansei engineering system. The feature of the presented method is that the nodes are defined as the rules which contain the classifier using GA. Linguistic fuzzy rules are then extracted from the induced decision tree. The linguistic rules inform the user of the relationships between human Kansei and design items. The fuzzy decision tree was able to represent the linguistic rules for forward and backward Kansei reasoning. We also proposed the knowledge acquisition using GA.

Our method was tested with an experiment on automobile design. The results from the experiment indicated that the proposed method accurately represented human perceptions of the comfort of vehicle interior space. The results created by the FDTGA are comparable to the results from conventional statistical methods. Despite the replacement of the optimal with the second optimal solution, the structure of the tree induced by FDTGA remains very stable. The results confirmed that the selected rules maintained the structure in the bit pattern of classifiers. It can be concluded that our method has the advantage that the structure of the generated tree and the representation of dependency among different variables well reflect the determination of the dimensions.

7. For further reading

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