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An Article Kansei Retrieval System Combining Recommendation Function and Interaction Design

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Abstract: In most article retrieval systems using Kansei words there exists a gap between user's Kansei and the system's Kansei model. Therefore, it is not always easy to retrieve the desirable articles. The purpose of this paper is to bridge this gap not to put a strain on users by combining the recommendation function and interaction design with four features. First, users can retrieve intuitively as the system visualizes retrieval space consisting of a torus type SOM (Self Organizing Maps). Second, users can find the most desirable article in any case by elimination methods to delete undesirable articles pointed by the user. Third, neural networks in the system learn user's Kansei based on the most desirable article to improve the retrieval accuracy. Fourth, users can search articles by arbitrary Kansei words, and can edit retrieval criteria as they please. In the evaluation experiments, the authors took actual paintings as the articles, and evaluated usability (*effectiveness*, *efficiency* and *satisfaction*), *novelty* and *serendipity*. These results were led by the synergetic effects of the recommendation function and interaction design.

Keywords: personalization, Kansei information processing, human computer interaction, Web retrieval, intelligent user interface

1. Introduction

Recent advancement of information technology has improved retrieval systems and recommendation systems of multimedia contents such as music and images. The demands for e-commerce have also become so high. Consequently, the article retrieval systems and article recommendation systems of multimedia contents are valuable. It is, however, not easy to give proper retrieval keywords for such contents. One way of retrieving them is to use adjective keywords called "Kansei words" to represent human feelings and impressions. For example, the BIGLOBE Kansei retrieval to find hot spring sites has already been put to practical use [1]. However, the accuracy of retrieval results is still insufficient due to the gap between user's Kansei and the system's Kansei model. In this paper, the gaps mean 1) the difference of expressions between the degree of user's Kansei and the degree of the system's Kansei model (e.g."Very," "Quite" and "Slightly" different), 2) the difference between user's desirable Kansei words and the system's default Kansei words, and 3) the flexibility of user's Kansei against the inflexibility of system Kansei model. In other words, user's Kansei is easy to be changed during and after search. For instance, users generally prefer never seen articles and unpredictable articles to the same articles shown repeatedly. These three differences are intimately interrelated in Kansei retrieval system. To bridge this gap, we consider that personalization of system is necessary. Personalization means that the service or technology provides appropriate information and forms suited for user's own taste [2]. In this paper, we approach personalization from two aspects: the recommendation function and interaction design. The recommendation function suggests user's desirable information. Specifically, we implement the function to revise the degree of Kansei word, and to accept arbitrary Kansei words. Moreover, it efficiently collects the teacher data to realize the function. Interaction design is a new discipline which comes from Human-Computer interaction and includes ergonomics, computer science, engineering, aesthetics, psychology and social sciences [3], [4]. Interaction design strongly relates to the retrieval process, and can be applied for the assistance of decision-making processes, visualization of recommendation methods, edit of the system, and so on. If the system realizes good interaction design, the system offers *conception* and *conviction* of users [5]. For this reason, to combine interaction design with the recommendation function can provide conviction about the process and result of the recommendation function. Moreover, it can provide conception in order to avoid the search from becoming trapped in a localized solution that causes users to repeat to show the same articles. In brief, these two methods are complementary and offer advantages to each other. Hence, we aim to implement them together. In this result, the system achieves the flexibility of user's Kansei.

User profiling is mainly applied to the recommendation function. Hijikata pointed out that user profiling methods can be classified as either explicit or implicit methods [6]. In the explicit method, users directly input the information about individual taste. In the implicit method, the system estimates the individual tastes based on past user behavior. As examples of explicit method in the recommendation function, individual tastes

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are estimated by the questionnaire in advance [7], [8], [9], and by asking users to grade the browsed Internet pages on their interest and relevance [10]. Such explicit methods put a strain on users. On the other hand, implicit methods infer individual taste by usage history [11], [12], [13], [14]. However, they need enough usage history and tend to confuse users because the system is automatically revised in the background. By visualization, the system we proposed avoids confusing the user [15]. However, the degrees of its freedom are low because it is limited to default Kansei words prepared by a system architect. Meanwhile, many examples about interaction design have been studied. Herlocker et al. examined the most useful information for customers to purchase movies [16]. Examples of interaction design that freely customizes the system's forms are iGoogle, My Yahoo!, S-Conart [5], Brusilovsky's study about adaptive hypermedia [17] and c-baseMR [18]. In these studies or services, improvements of usability are expected. However, it is difficult to decide system's goal because deep interaction between users and systems is required in order to find each user's goal. Thus, most studies implement one of the two methods. In contrast, studies combining both methods are rare. An example of where the two methods are combined is Otubo's study, which updates a recommendation list by graphical and edit operation [19]. However, Otubo's study supports only single preference index like "interested or not interested", and cannot support multiple indices like Kansei words.

In this paper, we propose a novel Kansei retrieval method which combines both the recommendation function and interaction design utilizing Kansei words. We take an implicit profiling method to reduce strain on users. However, implicit methods have unavoidable problems: it takes a long time to store adequate data for profiling, and static profiling accuracy by implicit methods are limited due to flexibility of user's Kansei during search. Therefore, users often abandon to use the system. To compensate the low accuracy, we combine interaction design with implicit methods. Thereby, the system provides conviction about the retrieval process and result by interaction design, and allows efficient retrieval.

We implement four features to realize the recommendation function and interaction design. First, the system visualizes retrieval space by a torus type SOM. In this way, users can search articles intuitively without confusion because users can observe the distribution of articles and the retrieval process. Second, the system avoids the search from becoming trapped in a localized solution by elimination methods. They allow users to select undesirable articles, and automatically eliminate non-selected articles in the display. In this way, users can find the most desirable article in any cases. Third, the system revises the degree of user's Kansei based on the most desirable article by a three-layered perceptron. Fourth, users can search articles by the arbitrarily added Kansei words. The parameters related to the added Kansei word are valued by using the support vector machine (SVM) method. In the result, we expect to improve the accuracy and flexibility of retrieval. If the system implements too many features, it is hard for users to use. Therefore, we implement a few features.

For the experiments, we developed an article retrieval support system implemented with the proposed method and employed artistic painting images for article database. To evaluate whether the system bridges the gap between user's Kansei and the system's Kansei model, we introduced three aspects of usability (*effectiveness*, *efficiency* and *satisfaction*), *novelty* and *serendipity* as the evaluation indices. The difference of expressions between the degree of user's Kansei and the degree of the system's Kansei model is evaluated by *effectiveness*. If effectiveness is high, user's most desirable article is easily found. Next, the difference between the system's default Kansei words and user's desirable Kansei words is evaluated by *effectiveness*, *novelty and serendipity*. If the system accepts user's desirable Kansei words, users can more closely search articles. Moreover, users can find unseen articles and unexpectedly interesting articles because a new retrieval space related to a new Kansei word is constructed. Third, the flexibility of user's Kansei against the inflexibility of the system's Kansei model is evaluated by *efficiency*, *novelty* and *serendipity*. If the system achieves flexibility of user's Kansei, efficiency of retrieval is improved because it avoids users from becoming confused and the search from becoming trapped in a localized solution. The system can also recommend unseen articles and unexpectedly interesting articles. S*atisfaction* is all-round metric. It can comprehensively evaluate about the three differences. In short, we consider that these three differences can be evaluated by five criteria.

2. Proposed System

Necessary matters of Kansei retrieval for implicit methods can be separately considered in the retrieval and learning parts, as follows:

- Retrieval part
  - not to confuse users
  - to avoid trapping in localized solution
  - to efficiently collect teacher data to profile
- Learning part
  - to fit the degree of the system's Kansei model to the degree of user's Kansei
  - to accept arbitrary Kansei words

With regard to the retrieval part, users are sometimes confused about their preferences of their desirable articles because user's criteria of Kansei words can be varied during the search. Therefore, the system needs to clearly show the current states of user's criteria. Moreover, the implicit method tends to confuse users because the system is revised automatically. Therefore, the system also needs to show users how it is revised. Second, Kansei retrieval system tends to become trapped in a localized solution because of diverseness of Kansei word's image and insufficient accuracy. Therefore, the system must compensate for the drawback, so that users can find the most desirable article in any case. Third, we aim to efficiently collect teacher data because the implicit method takes a long time until teacher data is stored adequately. In learning part, we implement the following two features: 1) to fit the degree of the system's Kansei model to the degree of user's Kansei and 2) to accept arbitrary Kansei words. Incidentally, we consider that the flexibility of user's Kansei is achieved if the system fulfills all of necessary matters.

According to the necessary matters, we implement four features. They include some characteristics for "recommendation methods (R)" and "interaction design (I)" as follows:

- Visualization by a torus type SOM
  R: clustering of articles
  I: map exploration with trajectory of retrieval process
  I: display the distribution of the Kansei parameter with color intensity
- Elimination methods
  R: undesirable articles selection
  I: display recommendation reason
  R: automatic elimination of non-selected articles
- Kansei leaning by neural networks
  R: optimization for initial search result
  I: display leaning result
- Addition of arbitrary Kansei words by SVM
  R: registration and usage of arbitrary Kansei words
  I: editable retrieval criteria

Figure 1 shows that which of characteristics in the two methods is related to which of necessary matters. The line width shows the strength of the relation. Necessary matters are achieved by combination of the two methods. In this chapter, each characteristic is explained in detail.

2.1 Visualization by a Torus Type SOM

Users search for desirable articles in the visualized retrieval space by SOM. A SOM is a type of artificial neural networks that is trained using unsupervised learning. In particular, a SOM is useful for clustering method and visualizing high-dimensional data in low-dimensional view [20]. In our method, the SOM is identified as the search space. The first reason why SOM is selected for the proposed system is that SOM realizes "smooth clustering" because it preserves the topological properties of the input space. When nodes of SOM are colored by values of Kansei parameter, it is easy to retrieve articles because the color intensity is not rapidly varied but consecutive (see Section 2.1.3). The second reason is that we can control the uniformity of article distribution by changing the learning step number or learning rate of the SOM (see Section 3.2). The third reason is that once the map learning is completed, it is not necessary to relearn the map even when the new articles are added in the database.

The Kansei parameters of articles are configured by the Semantic Differential Method using adjective pairs, such as "bright and dark". In this time, they are configured by the average of multiple user's Kansei obtained by the preliminary survey. Then articles are mapped to the two-dimensional retrieval space by a SOM. Here, we employ a torus type SOM which cyclically unites the output nodes so that users can explore without regard of the border [21]. At beginning of retrieval, users input values of the Kansei parameters of the desired articles. They are automatically mapped on the retrieval space by SOM, and the system displays the nearby articles of the mapped position. Users can search the most desirable article by selecting one of the articles in the display.

2.1.1 Clustering of Articles

We employ the clustering method because Kansei words are likely to represent multiple different aspects. Mukunoki et al. employ SOM in order to solve diverseness of Kansei word's image, and proved its effectiveness [22]. In our system, article's clusters are formed by the values of each Kansei word. As a result, users can get clues to find the desirable articles though unsuitable articles are recommended first. Meanwhile, if the number of articles increases, it is difficult to display all articles. In this case, the representative articles are automatically decided by clustering method, and displayed in the retrieval space. Therefore, the system can deal large amounts of articles without mess in the display.

2.1.2 Map Exploration with Trajectory of Retrieval Process

Users select a desirable article in the displayed retrieval space. Then the display area moves to center the selected article, and new surrounding articles are displayed. Users repeat this operation until the desirable article is found. In this way, users can keep search intuitively without inputting search criteria again. In addition, the system shows the trajectory of past movement in the retrieval space, and users can avoid wandering because users can know how they move panoramically in the retrieval space. **Figure 2** shows an overview of map exploration with trajectory. The human silhouette means the current position in the retrieval space.

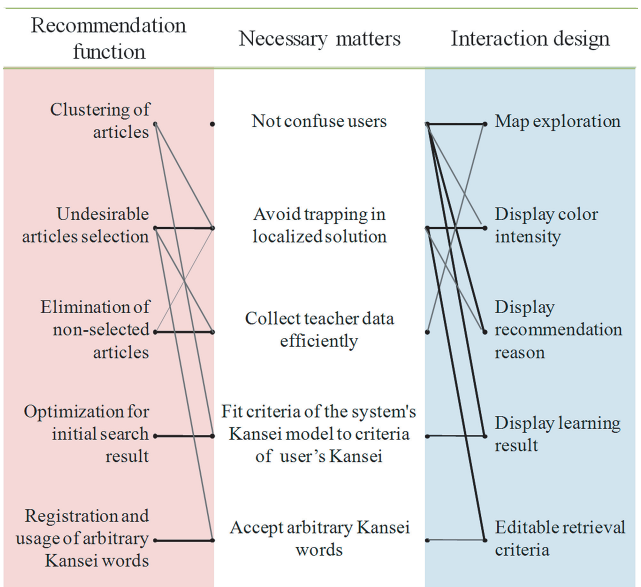


Fig. 1 Relationship between system characteristics and necessary matters.

Fig. 2 Map exploration with trajectory of retrieval process.

Fig. 3 Color intensity distribution of Kansei parameter.

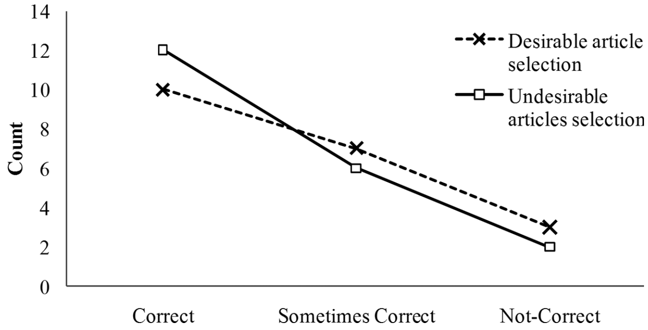


Fig. 4 Correctness about recommendation reasons.

2.1.3 Display the Distribution of the Kansei Parameter with Color Intensity

Users can select one of the Kansei parameters and view the value of the corresponding SOM element by color intensity. **Figure 3** shows an example of color intensity distribution of the Kansei parameter "bright and dark." In this way, the users can consciously search the important criteria. This characteristic exerts a synergistic effect on combining with other recommendation characteristics.

2.2 Elimination Methods

Elimination methods are used to allow users to remove undesirable articles. In this way, users can continue to search desirable articles if users cannot select ones. The system then displays recommendation reasons in order not to confuse users. Meanwhile, the system can also display more desirable articles than current ones by eliminating non-selected articles in the display. These features are useful for avoiding becoming trapped in a localized solution.

2.2.1 Undesirable Articles Selection

When it is difficult to select the desirable article in the display area, users can alternatively select the undesirable articles to eliminate from the retrieval space, and the system estimates user's tendency based on the "heuristic" rule known in the field of psychology. The "heuristic" rule means that we have a rough and quick decision unconsciously when we try to judge for a complex problem with limited time, knowledge and information processing ability. In particular, "availability heuristic" is a phenomenon that easily evoked elements are heavily emphasized on [23]. The elimination method is regarded as this heuristic process [24].

In our system, the Kansei parameter which is the most different from the initially input search criteria is supposed to be the most important element of the desirable article, because it is possibly evoked easily. The system then increases the weight of the element of the SOM and reconstructs the SOM. In this reconstruction, articles eliminated by users are not included and it can be quickly processed by the plasticity characteristic of the SOM. After this reconstruction, the system displays the articles depending on user's tendency. In this way, users can continue the efficient search to reach the most desirable article by pointing the undesirable ones. This function is also useful for adding arbitrary Kansei words because the system needs not only fitting articles but also not fitting articles related to the Kansei words.

2.2.2 Display Recommendation Reason

Our system displays for users which Kansei word is preferred for the current search as the recommendation reason. The Kansei word to display is predicted by "heuristic" rule when undesirable articles are selected. Thereby, the system reduces the prediction mistake because users then search articles by only the current important Kansei word. For confirmation, we conducted a pre-survey about displaying recommendation reason. 20 people tried them, and answered whether the recommendation reason was correct or not incorrect when undesirable articles were selected. We compared it with the case in which desirable articles were selected by map exploration or elimination of non-selected articles. In this time, the Kansei parameter which is the most closely related to the initially input search criteria is regarded as the most important Kansei word. The result is shown in **Fig. 4**. It shows that the system can almost estimate the most important element. Moreover, more users answered "correct" than the map exploration and the elimination of non-selected articles. In the result, we validated estimating method based on the "heuristic" rule.

The system should not display extraneous information because it decreases user's satisfaction [16]. Therefore, it is important to reduce prediction mistakes. Consequently, it can prevent user's confusion by SOM reconstruction because user's current preferences are clarified.

2.2.3 Automatic Elimination of Non-selected Articles

After users select an article during search, the unselected articles in the display are removed from the candidates to search. Thereby, the system makes the search more efficient. However, this operation could leave no article in the display area and make the search impossible. To avoid such situation, the system reconstructs the retrieval space to get smaller. The number of the output SOM nodes is decreased in proportion to the number of total remaining articles, and the retrieval space gets smaller. Then, the out-of-display articles resembling the selected article gather into the display area. Users can also select the same article after reduction, if newly displayed articles are not preferred. This operation can be repeated until more preferred articles are displayed. In this way, users can select more articles and keep search without losing articles in the retrieval space. This method is useful for avoiding becoming trapped in a localized solution.

2.3 Kansei Learning by Neural Networks

There is always a difference between the degree of user's Kansei and the degree of the system Kansei model. In other words,

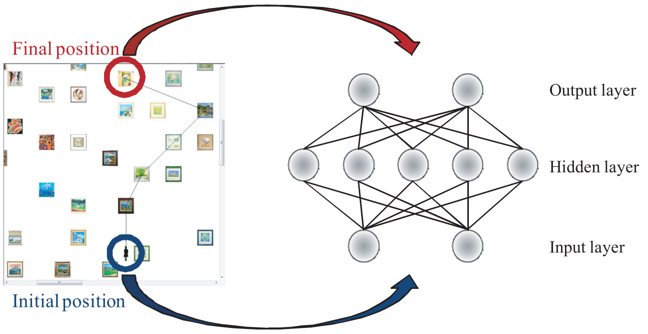


Fig. 5 Kansei learning by neural networks.

the initial input Kansei parameter values do not match the values of the desirable article in the system database at the beginning. Therefore, it is difficult to instantly find the desirable article just by the initial input. We employ neural networks to bridge this gap. Neural networks can manipulate non-linear statistical data like Kansei information. Some studies related to Kansei retrieval system employ neural networks, and get good results [7], [25].

2.3.1 Optimization for Initial Search Result

The system learns the relationship between the initial input retrieval criteria's coordinate value and the finally selected article one. The learning is performed using a three-layered neural networks using a backpropagation algorithm. The input data is the initial position on the map, and the teacher data is the position of the article finally selected. By employing map's position as learning data, the system can quickly learn by two-dimension data if arbitrary Kansei words are added. After learning, the initial position is shifted by the neural networks, but the map of SOM is not warped to avoid the user's confusion in the retrieval space. **Figure 5** shows the relationship between input and teacher data for the neural networks.

The neural networks give the revised mapping around the learning data position, while mapping should not change at the place far from the learning data. Therefore, the identical mapping data are selected randomly and mixed in the learning process. The learning rate ε for identical mapping is defined as,

$$\varepsilon = \alpha \frac{\sum_{i=1}^{T} (\mathbf{a} - \mathbf{b}_i)^2}{T^2} \quad (1)$$

where, $\mathbf{a}$ is the position of the identical mapping, and $\mathbf{b}_i (i = 1 \ldots T)$ is the position of the learning data which the user has input for past retrieval. T is the total number of learning data. α is the normalization factor to set ε into [0,1]. This formula gives a larger learning rate when the average distance from practical learning points is larger. As a result, the identical mapping is kept at the points around which no learning input data exists.

2.3.2 Display Learning Result

The system in the implicit method is occasionally revised despite the intention of users. Even if the revision works properly, the system sometimes confuses users because it performs automatically. To avoid these problems, the system displays the trajectory of the initial position's shift. In the result, we expect not to confuse users by showing how the system is revised. Moreover, users can also cancel the revision if it does not work properly.

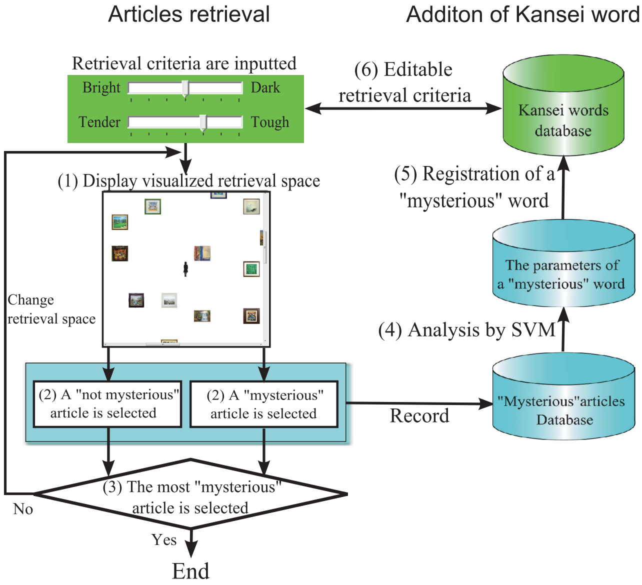


Fig. 6 The schematic diagram of proposed system.

2.4 Addition of Arbitrary Kansei Words by SVM

Most users wish to search articles not only by given Kansei words but also by their own desirable Kansei words. However, the system cannot prepare all Kansei words in advance because most of the words and expressions have the potential to be utilized as Kansei words. Therefore, the system needs to accept arbitrary Kansei words. However, the system must parameterize the arbitrary Kansei word in accordance with all articles, which is laborious. Meanwhile, Mukunoki et al. reported that some typical and popular Kansei words can express other Kansei words [22], although it needs images selected by specialists in order to add arbitrary Kansei words. We suggest a new procedure to treat arbitrary Kansei words by utilizing the given default Kansei words.

2.4.1 Registration and Usage of Arbitrary Kansei Words

Figure 6 shows the schematic diagram of the proposed system in case of adding an arbitrary word "mysterious." First, the proposed system needs to find out which articles fit the added Kansei word for users as teacher data for supervised learning. The fitting articles are selected by the characteristics mentioned in Section 2.1.2 or 2.2.3. On the other hand, the non-fitting articles are selected by the characteristic mentioned in Section 2.2.1 ((2) in Fig. 6). This operation continues until users find the most fitting article for the added Kansei word, or select a sufficient number of articles. The user's strain to collect teacher data is minimized because the system can simultaneously collect the teacher data while users repeat the selection to find the most desired article. At this stage, the articles fitting the added Kansei word are scored by +1. On the other hand, the articles not fitting it are scored by −1. After the teacher data are collected enough, the system estimates the parameters of the added Kansei word by SVM. The added Kansei word is registered as retrieval criteria in the same way as the default Kansei words after this procedure. Additionally, the system can also create the new retrieval space concerning the parameters of the added Kansei word. Therefore, the system can create an opportunity to find unknown desirable articles as unexpectedly interesting articles. The parameters related to the added Kansei words are learned by neural networks in the same

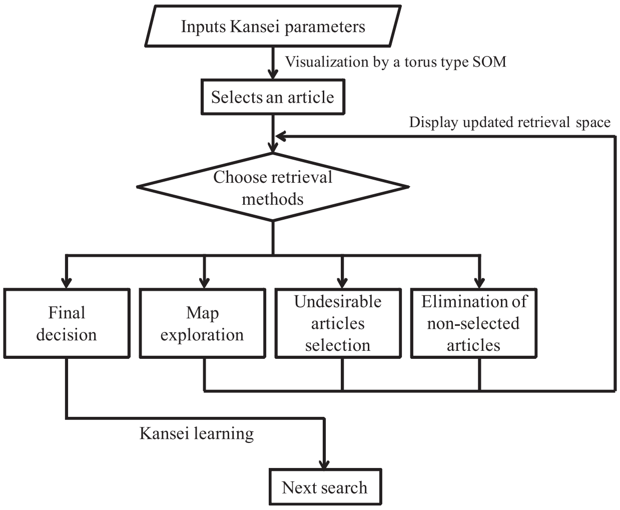


Fig. 7 System's usage flow.

way as the system's default Kansei words because the added Kansei words are often the low accuracy.

2.4.2 Editable Retrieval Criteria

Users can take an advantage of arbitrary Kansei words added by themselves. Besides, Kansei words added by other users are also available as own retrieval criteria by accessing the database which stores the values of each added Kansei Word. Therefore, users can edit retrieval criteria as they please ((6) in Fig. 6). Users can also observe the added Kansei word's distribution by color intensity.

3. Implementation

Figure 7 shows the usage flow of our proposed system. At beginning of retrieval, a user inputs values of the Kansei parameters of the desirable articles, as retrieval criteria. They are automatically mapped in the retrieval space. The system displays the nearby articles of the mapped position. A user then searches the most desirable article selecting repeatedly a article by retrieval methods: map exploration, undesirable article selection and elimination of non-selected articles. If the most desirable article is decided by a user, the system automatically learns the individual taste and revises the system's Kansei model to fit the user's Kansei by three-layered neural networks.

3.1 Article and Default Kansei Words

We made some experiments to evaluate the proposed retrieval system for paintings to assist the customers who wish to buy paintings. In case of painting selection assistance the proposed system has some advantages. 1) The judgment is taken easily with visual display. 2) Users without specialized knowledge can select instinctively with Kansei words. 3) The Semantic Differential Method can be easily implemented for evaluation. In the experiments, 100 landscape and 35 abstract paintings were stored in the database. Abstract painting images especially have difficulty in searching by keywords. Thereby, Kansei retrieval is predictably effective. Total 135 painting images were rated by 20 persons in 7-point scale of eight adjective pairs shown in **Table 1**. The adjective pairs were chosen according to the Inoue's study on Kansei evaluation of paintings [26]. The average of human evaluation was set into the system database in advance as the initial system Kansei model. The system also allows users to add arbitrary Kansei words based on this eight adjective pairs.

Table 1 Pairs of Kansei word.

Pair #	*Word 1*	*Word 2*
1	Bright	Dark
2	Tender	Tough
3	Cheerful	Melancholy
4	Fancy	Plain
5	Complicated	Simple
6	Sharp	Dull
7	Warm	Cold
8	Comfortable	Uneasy

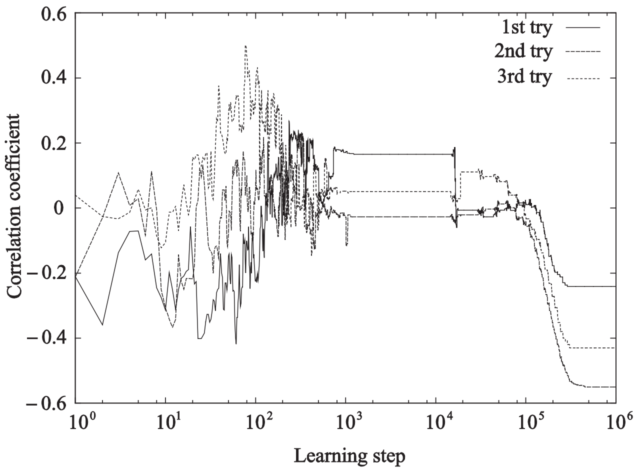


Fig. 8 Correlation coefficient for each learning step number.

3.2 Parameter Configuration

We set the initial number of the output nodes of the torus SOM. If it is small, the painting articles get crowded in the retrieval space and it is difficult to view. On the other hand, if it is large, the paintings are distributed sparsely and it takes a long time to search. In this experiment, the number of the nodes was empirically set to 30×30, although the user can configure different number by preference.

The uniformity of article distribution in the whole retrieval space is important for search from the entropy point of view. The retrieval efficiency depends on the initial construction of retrieval space given by the SOM. Consequently, we examined the suitable learning step number of the SOM construction. We calculated the correlation coefficient between x and y coordinates values of the distributed articles changing the learning step up to 10^6. The smaller absolute value of a correlation coefficient means the more uniform distribution. **Figure 8** shows the result of correlation coefficient values of three trials, where learning rate is 0.1. The correlation coefficient is unstable up to 10^3 steps, and it gets down from 10^5 steps because of overfitting. The correlation coefficient is stable between 10^4 and 10^5 steps. Therefore we set the step number to 30,000 which is nearly the median in logarithmic scale.

In the elimination method, the initial weights of the Kansei parameters are set to 1. Every time a user executes the elimination method, the weight of Kansei parameter regarded as the most important is incremented by one. The learning step for the elimination method is set to 6,000. The color intensity is displayed in proportion to the value of the SOM element.

Three-layered neural networks are used for Kansei learning with 5 hidden neurons. The number of iterative learning is 80,000. Every 400 times, the learning data is used once. In the other steps, identical data are learned. Learning rate is set to 10, and the rate for the identical learning is set to ε according to the Eq. (1) mentioned in Section 2.3.1.

We utilize the software library LibSVM for SVMs modeling [27]. We run a preliminary experiment to avoid overfitting. In the result, we choose the C-SVM with RBF kernel. If teacher data exist only in one side, we choose one-class SVM. Cost parameter is set to 2. υ parameter are set to 0.1. Other tool parameters are set to the default values of the LibSVM.

3.3 Application Software

We developed an application system by implementing the proposed features. First, a user inputs 8 adjective words value by 7-step track-bars and the system directly displays the painting images in the retrieval space centering the initial position mapped by the SOM. At the initial position, human silhouette is drawn as shown in Fig. 2. If two or more articles are mapped to the same position, the system displays the description "two or more articles" above the image. When the user clicks a painting image, a new dialog with the zoomed image is shown. If the user clicks the position where two or more articles overlap, new multiple dialogs are shown all at once. Subsequently the user can choose one of five buttons for three retrieval methods and two basic operations: map exploration, undesirable article selection, elimination of non-selected articles, final decision and cancel. When the user chooses final decision, Kansei learning by neural networks starts automatically. At this time, the user can select the Kansei word to color by checking the appropriate box. The user can also select whether recommendation reason is displayed and learning result is displayed. Moreover, the user can shift the display area by drag and drop, and can expand and shrink by a scroll wheel of a mouse. If the user wants to add a new Kansei word, the user inputs the new Kansei word in the text-box. The user then searches articles about the new Kansei words by default Kansei words. After the user finds the most fitting article about the new Kansei word, or selects a sufficient number of articles, the user clicks "create new Kansei words" button. In the result, the values of the new Kansei word are automatically reserved in the database. The user then clicks "add new Kansei word" button to use the new Kansei words as retrieval criteria. At this time, the user can also add Kansei words created by other users in the database.

4. Evaluation Experiments and Results

Some users actually used the implemented software mentioned above, and evaluated usability of whole system and each function. Although usability was defined by many people, we employed ISO's broad definition of usability consisting of three distinct aspects [28]. The three aspects should be considered independently in retrieval systems, and all be included in usability evaluation [29].

- *Effectiveness*: the accuracy and completeness with which users achieve certain goals. In this paper, we compared the resultant positions of Kansei learning with the initial positions or we performed subjective assessment.
- *Efficiency*: the relation between the accuracy and completeness with which users achieve certain goals and the resources expanded in achieving them. In the paper, we measured click count and time to search a randomly chosen painting.
- *Satisfaction*: the user's comfort with and positive attitudes towards the use of the system. In the paper, we performed subjective assessment expressed by a grade on a five-point scale. We also argue about the theory of customer experience to closely analyze satisfaction of retrieval process.

Customer experience is defined in some discussions [30], [31]. In this paper, we employ a narrow interpretation of customer experience, which is the value gained from the process purchasing of articles. Customer experience is the important factor in the Kansei retrieval system because Nagasawa points out the effectiveness of Kansei engineering as an engineering approach of customer experience [32]. We hypothesize that correspondence of flexibility of user's Kansei needs to create their own desirable retrieval process in view of Customer experience. We implemented the characteristics of interaction design to freely edit the system by users, and create own desirable process of searching articles. Accordingly, we expect to improve satisfaction by realizing user's desirable retrieval process.

We also employed *novelty* and *serendipity* metrics [33], [34]. They can measure the "non-obviousness" of the recommendations as an important metrics for user's satisfaction. Theses metrics indicate whether the recommended item is both unknown and favorite. We evaluated that how many unknown desirable articles about a new Kansei word are recommended. A serendipitous recommendation helps users to find an unexpectedly interesting item which might not be discovered in other way. For measuring serendipity, it is necessary to evaluate how the recommended items attract and surprise the user. However, no concrete calculation method has been proposed so far. Therefore, subjective assessment was adopted.

4.1 Evaluation for the Whole System

37 persons used both the proposed system and typical comparison system. The comparison system just retrieves articles without the features of interaction design. It merely shows paintings of Kansei parameters resembling retrieval criteria in order. We asked satisfaction of the proposed system and evaluation compared to the comparison system. The evaluations were rated in five-level from "Very Poor" to "Excellent." Here, we defined "Good" and "Excellent" evaluations as "be satisfied." **Table 2** shows the ratio of each impression, respectively. It indicates that nearly every person was satisfied with the proposal system, and gave higher evaluation to the proposed system than the comparison system. In the result, we confirmed synergetic effects of the recommendation function and interaction design.

4.2 Evaluation for Each Index

23 persons used the features of proposed system and evaluated

Table 2 System evaluation.

(a) Impression for system

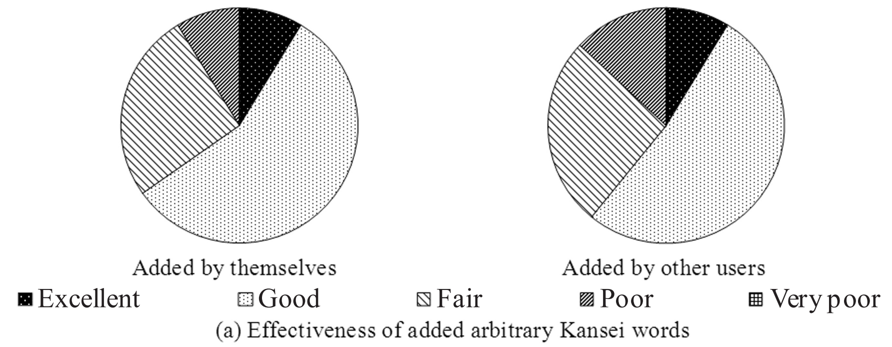
Evaluation	*Excellent*	*Good*	*Fair*	*Poor*	*Very poor*
Rate	10.8%	75.7%	8.1%	5.4%	0.0%

(b) Relative impression to comparison system

Evaluation	*Excellent*	*Good*	*Fair*	*Poor*	*Very poor*
Rate	43.3%	48.6%	8.1%	0.0%	0.0%

Table 3 Result of by Kansei learning.

	Without Kansei learning	*With Kansei learning*	*Difference*
Average (5 times try)	5.94	5.06	-0.88



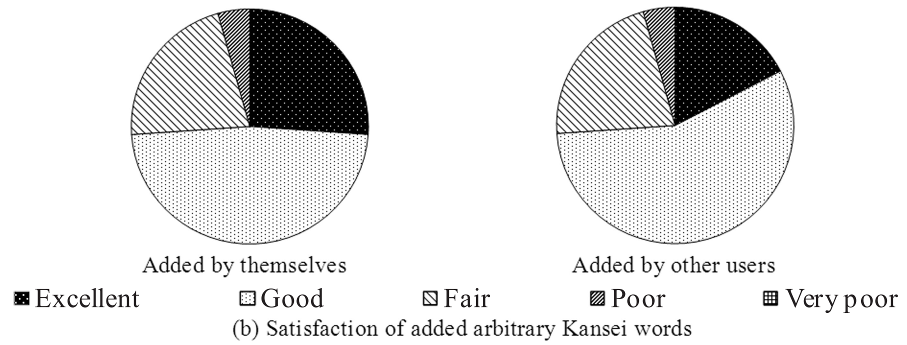


Fig. 9 The effectiveness and satisfaction for added Kansei words.

the five indices (*effectiveness*, *efficiency*, *satisfaction*, *novelty*, and *serendipity*).

4.2.1 Effectiveness

We evaluated the function of Kansei learning. Users tried retrieving their preferred paintings five times with the system's default Kansei words and arbitrary Kansei words added by themselves. Afterward, users tried retrieval and we compared the resultant positions of Kansei learning with the initial positions. The result is shown in **Table 3**. The first and second columns represent the distance values between the initial position and the finally selected position with Kansei learning. The unit is the SOM node distance. The third column indicates the difference. The initial position gets about 0.88 closer to the selected article in average. It can be concluded that the system fits to individual user's preference in the course of using the system.

Second, we asked effectiveness of a Kansei word added by users. We also asked effectiveness when users utilized Kansei words added by others users. The result is shown in **Fig. 9** (a). We can conclude that added Kansei words are useful because about 60% of the users feel that effectiveness is high. Moreover, the case of low effectiveness has some improvements by neural networks. However, effectiveness improvement has a limitation due to flexibility of user's Kansei during search. Here, we consider that the system needs to compensate the inadequate effectiveness by interaction design.

4.2.2 Efficiency

We quantitatively evaluated the search operation of the map exploration with trajectory of retrieval process and the elimination of non-selected articles. Users tried to search a randomly chosen painting by the map exploration, the elimination of non-selected articles and the comparison system. In each case, the click count and time until the finish were measured. If the click count was over 30 or the time was over 180 seconds, the search operation was discontinued and treated as 30 click count and 180 seconds. **Table 4** shows the result. The proposed system can retrieve quicker than the comparison one, and the elimination of non-selected articles can drastically reduce click count. Achievement rate of proposed system was also higher. It is to be noted that interaction design directly has no relation with effectiveness of recommendation. However, the system can reduce click count and time by interaction design. In brief, we showed that interaction design can compensate inadequate accuracy of recommendation.

Table 4 Retrieval performance for each method.

		Click count	*Time(s)*	*Achievement rate*
Proposed system	Map exploration	9.0	58.9	91.2%
	Automatic elimination of non-selected articles	3.4	34.6	96.5%
Comparision system		14.9	84.0	75.5%

Table 5 Satisfaction for selecting undesirable articles.

Evaluation	*Excellent*	*Good*	*Fair*	*Poor*	*Very poor*
Rate	52.2%	34.8%	13.0%	0.0%	0.0%

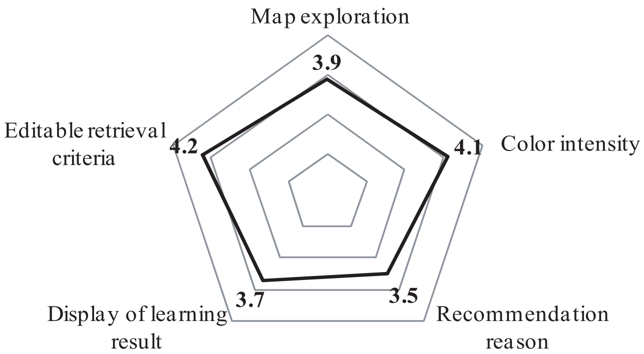


Fig. 10 Satisfaction for interaction design features (very poor = 1, excellent = 5).

4.2.3 Satisfaction

First, we asked satisfaction level about undesirable articles selection. The result is shown in **Table 5**. About 90% of users were satisfied. Though the system can estimate important Kansei word in a high rate, a few users emphasized the different Kansei elements from the retrieval criteria. We consider that such users can be supported by editing retrieval criteria as they please.

Second, we asked satisfaction of a Kansei word added by users. We also asked satisfaction when users utilized Kansei words added by other users. The result is shown in Fig. 9 (b). We can conclude that addition Kansei words are useful because over 70% of the users are satisfied with it. Though effectiveness of Kansei words added by other users are inadequate, satisfaction level is high. Interestingly, some users commented "it is fun to feel other user's Kansei though the accuracy is low."

Third, we evaluated satisfaction of interaction design characteristics: map exploration, search with the color intensity, display of recommendation reason, display of learning result, editable retrieval criteria. The result is shown in **Fig. 10**. We can conclude that interaction design improves satisfaction. In particular, display color intensity and editable retrieval criteria are excellent results. Here, we discuss this reason from the theory of customer experience. Evaluation of Customer experience is difficult because of an ambiguous concept. However, a majority of user's comments were: "The input of Kansei parameters come easy," "I am interested to feel other user's Kansei when I use a new Kansei word added by other users." For this comment, user's satisfaction increases not only by finding desirable articles but also by customizing the retrieval criteria and retrieval process. Users can make own retrieval process by display color intensity and editable retrieval criteria. Therefore, we consider that these methods grossly improve satisfaction. In other words, the creation of user's desirable retrieval process contributes to correspondence of the flexibility of user's Kansei.

4.2.4 Novelty and Serendipity

We evaluated *novelty* and *serendipity*. We asked users to show the articles that fit to the new Kansei word in the database. We then eliminated teacher data utilized for creating the new Kansei word. We consider that these articles are regarded as novel articles because they are unknown but fit to the Kansei word. We evaluated the precision, recall and F-measure of novel articles. Here, if the values of a new Kansei word by SVM were above 0.85, they were regarded as fitting articles. The result is shown in **Table 6**. The precision of Hijikata's system specialized for novelty is about 0.33. However, the precision of typical system non-specialized for novelty is under 0.1 [33]. Therefore, our proposed system showed better results than non-specialized system in novelty. Moreover, the adjectives having high "evaluation factor" (e.g., *likeable, good* and *beautiful*) are generally difficult for utilizing as retrieval criteria because there are great differences between individuals. However, users can occasionally find unknown desirable articles.

Next, we evaluated serendipity by subjective assessment about the function of retrieval part, and the response to the flexibility of user's Kansei during search. We also evaluated only the feature accepting arbitrary Kansei words, and the response to the flexibility of user's Kansei after search. The result is shown in **Table 7**. Most of users answered "rather yes" about the function of retrieval part. As reason, the system avoids users from trapping in localized solution by selecting undesirable articles and so on. Meanwhile, more users answered "yes" about only the feature accepting arbitrary Kansei words. We consider that the system created a new retrieval space concerning the values of the added Kansei word, and made an opportunity to find unexpectedly interesting articles. Besides, users were not confused in the new retrieval space because users could expeditiously figure out the new retrieval space aspect by display color intensity and so on. In the result, we concluded that the Kansei retrieval system needs to combine the recommendation function and interaction design in order to efficiently find articles with novelty and serendipity.

5. Conclusion and Future Work

We have proposed an article Kansei retrieval system to bridge the gap between user's Kansei and system's Kansei model by combining the recommendation function and interaction design. We take an implicit profiling method to reduce a strain on users. The system is implemented with visualization by a torus type

Table 6 The novelty for arbitrary Kansei words.

Persons	*Added Kansei words*	*Novelty* *Precision*	*Recall*	*F-measure*
1	*Mysterious*	0.50	0.43	0.46
2	*Boisterous*	0.33	0.50	0.40
3	*Enjoyble*	0.63	0.29	0.40
4	*Mild*	0.80	0.19	0.31
5	*Realistic*	0.38	0.26	0.31
6	*Calm*	0.42	0.21	0.28
7	*Natural*	0.33	0.24	0.28
8	*Unusual*	0.43	0.20	0.27
9	*Colorful*	0.20	0.43	0.27
10	*Disorganized*	0.17	0.50	0.25
11	*Cute*	0.18	0.25	0.21
12	*Expansive*	0.30	0.13	0.18
13	*Realistic*	0.10	0.20	0.13
14	*Loose*	0.11	0.17	0.13
15	*Colorful*	0.08	0.38	0.13
16	*Enigmatic*	0.06	0.33	0.10
17	*Healing*	0.13	0.08	0.10
18	*Smart*	0.00	0.00	0.00
19	*Enjoyble*	0.00	0.00	0.00
20	*Likeable*	0.29	0.29	0.29
21	*Good*	0.25	0.16	0.20
22	*Beautiful*	0.13	0.13	0.13
23	*Beautiful*	0.17	0.06	0.09
Average		**0.26**	**0.24**	**0.25**

Table 7 The serendipity for system.

(a) The serendipity for the function of retrieval part

Evaluation	*Yes*	*Rather yes*	*Undecided*	*Rather No*	*No*
Rate	13.0%	56.5%	21.7%	4.4%	4.4%

(b) The serendipity for the feature accepting arbitrary Kansei words

Evaluation	*Yes*	*Rather yes*	*Undecided*	*Rather No*	*No*
Rate	39.1%	39.1%	13.0%	4.4%	4.4%

SOM, elimination method, Kansei learning by neural networks, accepting arbitrary Kansei words. In the experiments, we evaluated usability, *novelty* and *serendipity* about these features and the total system using painting images as search article. We confirmed that the system could make the initial position closer to the desirable article from previous retrieval results by neural networks. The click count and search time were smaller than the typical retrieval system. Most of users were satisfied with the usage of visualization and elimination method. Additionally, we confirmed the improvement of satisfaction, *novelty* and *serendipity* by adding new Kansei words. We conclude that these results are led by the synergetic effects of the recommendation function and interaction design.

We are trying to apply the developed system for other different article retrievals to examine the universality of the proposed method. In the future, we would like to link physical parameters to Kansei factors, and to implement the automatic indexing of articles.

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