Interactive Recommender System to Estimate Personal User's Kansei Model

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***Abstract*—The purpose of this research is to develop recommendation system reflecting individual user's Kansei model. In the target contents have some keywords. The proposed method has following features. A recommendation problem is formulated as an optimization problem. The design space is defined with keywords of contents. The distance of each keyword is calculated by the network information which is developed by the whole contents in the system. The evaluation values of contents is derived by the interaction operation between the system and a user. The landscape of evaluation values in design space is called "Kansei Model" in this study. Using Kansei model information, an optimum point which is a recommendation content is extracted by interactive evolutionary computation (iEC). To analyze generated networks and investigate tendency of recommendation results by the proposed method, subjective experiment was performed by using large-sized product dataset. In the experiment result, it was confirmed that the proposed method could recommend products fitting subjective Kansei model.**

Keywords; recommender system, Kansei model, interactive evolutionary computation, keyword extraction

I. INTRODUCTION

The development in information technology has cast a flood of information on web. When a user browses information, it is difficult to attain proper contents that a user requests out of enormous data. For this reason, recommender systems are embedded in some online shopping and news sites, so that a user can be offered various recommendation contents individually [1], [2]. Recommender systems are categorized into two groups depending on their approaches; Collaborative filtering, and Content-based filtering. The former is the method in which the recommendations are made by finding the relevance between contents using the past behaviors and habits of all the users. Since the algorithm is based on the similarities of preferences among users, there is a case that a user is recommended items a user has never known before [3]. The latter is the method in which the contents a user prefers are predicted by storing the metadata, which is held within contents, as feature vectors [4]. Large-scale systems mainly use the former method; Collaborative filtering. Collaborative filtering is the method to find a preference pattern which is similar to the subject user out of large number of users. This means that it is difficult to adjust the recommendations so as to fit an individual user. As one of the methods to personalize the recommender system, building an individual Kansei model has been studied, so that it must be possible to make recommendations to fit the preferences and habits of individual users. One of the recommender systems uses the users' preference models; for example, users' gender, ages, the genres of preferred merchandises, and so on, are entered or assumed, so as to build models of a users' preferences [5]. However, this modeling method can deal only the preferences already determined, and it cannot deal with individual users' preferences. In this study, the recommender system is designed and constructed to meet users' Kansei by embedding a factor of interactive genetic algorithm [6], using feature vectors of contents as design variables. For example, for a user who is interested in two different kinds of domains, the proposed method would not recommend an item which is similar to the features of each domains, but would recommend an item based on the concept which is derived from an association with these features, so that the system would give a user an awareness of a new item. The traditional recommender system using the genetic algorithm configures the parameters that users want by optimizing the design variables using genetic procedures; the design variables are consisted of all the feature values an item has, and their weight is optimized using users' past behavior [7], [8]. In this method, it is considered that its precision of solution searches gets worse as the number of design variables gets larger. The reason of this characteristic is that all the feature values are treated in different dimensions on design variables space. Since each of design variables has not been defined their relationship among them, the feature values cannot be processed with genetic procedures, and they are required to be treated in different dimensions. A crossover method which merely switches the part of factors of feature value vectors has developed, but it cannot run the neighborhood search at a satisfactory level, because the switched factors do carry the feature values that parent individuals have [8]. For that reason, the traditional method would recommend an item similar to its parent individual, but it is difficult to recommend an item which conceptually connects both of its parent individuals.

In this research, a method is proposed in which genetic procedures are practicable between different dimensions, using "a contents parameter network". In this contents parameter network, each of words would have the relationship among other words to make a graph and the graph would be the neighborhood definition of a feature word. This method should be able to recommend an item using the concept newly generated from the feature values of parent individuals, so that the recommended item should have the various and instinctive connection with users' preferences. In order to verify the effectiveness of this proposed recommender system, a simulated experiment has conducted using the information of books at an online shopping site (Rakuten-Ichiba; Rakuten-Ichiba is the largest e-commerce site in Japan, which is run by Rakuten Inc., a Japanese e-commerce company.).

II. RECOMMENDER SYSTEM

A. Collaborative Filtering

There are several methods in Collaborative filtering; "User-based filtering" is a method which selects a user having a similar past behaviors out of multiple users, and recommends items the selected user has already browsed. "Item-based filtering" is a method which selects similar items by the method described above. Since Collaborative filtering is based on the similarity of preferences between users, there is a case in which a system recommends items unknown to the user. Collaborative filtering can be easily implemented, because forecasting and recommending do not require the priori information of items. It is also applicable to the system in which various items from multiple fields are mingled together. However, one of the restraints of Collaborative filtering is that all the items must be evaluated by users, so that there must be so many users. Therefore, an item nobody has evaluated yet has relatively lower possibility to be recommended, and sometimes recommendations are heavily concentrated on an item, which is a major defect of Collaborative filtering has. Collaborative filtering is mainly implemented to large-scaled systems, such as Google and Amazon [1], [2].

B. Content-based Filtering

Content-based filtering is the method which matches a feature vector to another; one of the feature vectors is user's past behavior, and another vector is meta-information of an item, such as authors, publishers, contexts, and so on. Since the recommender system does not require users' evaluations, all the items are equally recommendable, and it is applicable to small-scaled systems. A problem of content-based filtering is that recommendations are clustered on some items when the method simply recommends similar items having the same properties.

In order to overcome this defect, Fuzzy method which presents items having the similar concepts is sometimes applied to a content-based filtering [9].

C. The preceding studies of the personalized method on recommender system

In the former studies, it is concluded that the content-based filtering, described above, is useful as a method of building a Kansei model of an individual user [4]. However, in order to make personalized recommendations based on user's preference, it is required to study and predict a Kansei model which represents user's preference [10]. The typical methods are Bayesian Network [11] and Hidden Markov Model [12], which are based on probabilistic inference. Interactive genetic algorithm is also known as a method of building a Kansei model, which estimates and optimizes the parameters of elements that a user needs.

III. KANSEI MODEL AND INTERACTIVE GENETIC ALGORITHM

A. Kansei Model

A Kansei model which represents a model of psychological preferences that individual human being has. In this research, it is assumed that it is possible to represent a Kansei model using a function. In this research, the parameters of this function are called Kansei parameters, and the view of the function is called Kansei landscape. In this assumption, the item corresponding to the maximum value in the Kansei model should be evaluated as the best matching item to the user's preference.

A Kansei model is explained using an example of designing T-shirts in Fig.1. In this example, it is assumed that a T-shirt can be defined with 2 content parameters; a color and a pattern of a T-shirt. Generally, users do not comprehend their own Kansei parameters nor Kansei landscape as a whole. If a Kansei parameter space can be projected onto a content parameter space, a Kansei landscape can be drawn on a content parameter space. Thus, it should be possible to determine a T-shirt the user prefers by estimating the value of content parameters corresponding the maximum value on the Kansei landscape.

On the other hand, a value of Kansei model, which is a value of the function, is originated from Kansei. It is required to develop a method to evaluate user's Kansei, and interactive genetic algorithm is used for this evaluation in this research.

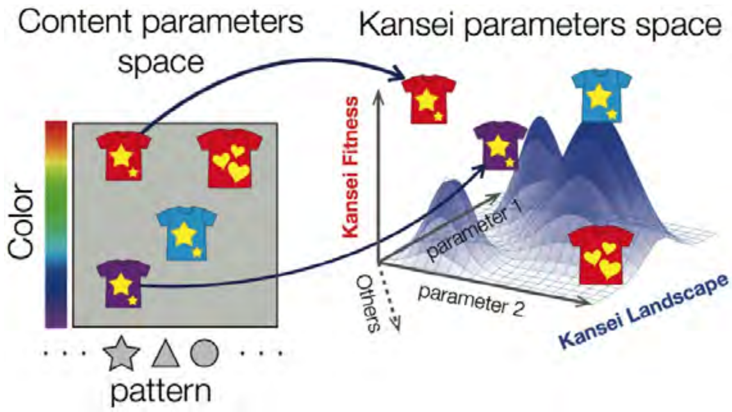

Fig. 1 An example of a Kansei landscape

B. *Interactive Genetic Algorithm*

Interactive Genetic Algorithm (iGA) is an interactive optimization method based on Genetic Algorithm (GA) which is known as an optimization algorithm for multipoint searches. In this research, a Kansei model is assumed as a landscape (slope) on the design variables space, and the best point or the best area is to be searched. The outline of iGA is shown in Fig. 2.

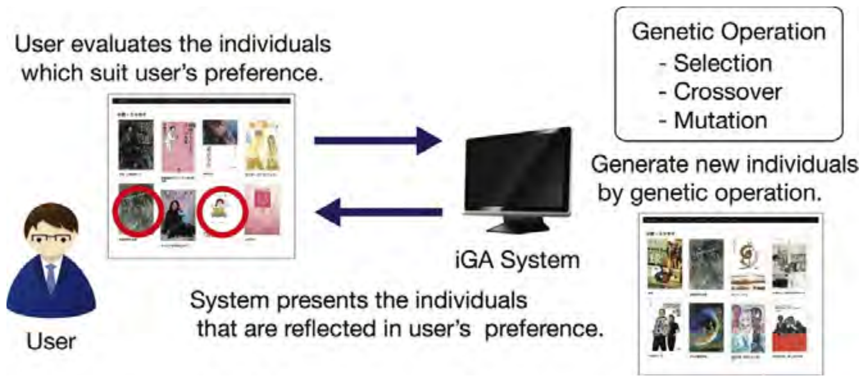

Fig. 2 An outline of Interactive genetic algorithm

The system which iGA is implemented presents multiple candidate solutions, so that users can evaluate these candidate solutions by their Kansei or preferences. In GAs, candidate solutions are called individuals. Then, the system applies genetic procedures based on the user's evaluations; the system generates new individuals from the old individuals which have been highly evaluated by the user, so that the each of the new individuals would have inherited their new individuals' nature. The system will present the generated individuals to the user for his/her further evaluations. In GAs, new individuals are called children and old individuals are parents. A group of individuals is a population. By repeating these procedures, the whole population would be transformed into the solutions that the user prefers.

iGA is practically applied to applications that require Kansei evaluations. For example, iGA has been applied to lighting designs of 3DCG [13], designs of hearing aids fitting [14], support of designing T-shirts [15], [16] or Yukata [17] and so on, and these applications turned out to be highly successful.

In iGA, design variables which express a design candidate should be prepared. For example, in a support system for clothing designs, the following factors are defined as design variables; patterns, colors and accessories of clothing. Then, each solution is composed of vectors of these design variables. In the genetic procedure phase in which optimization is processed, these design variables are modified into a binary digit string, a type of a gene and a chromosome, such as values of real number, to be used in the procedure. At the beginning of a trial, a population containing multiple chromosomes is initialized. This initialization is performed in random. Then, a user makes evaluations on each of these chromosomes. Receiving the evaluations, the system selects a chromosome having a high evaluation as a parent individual, and gives a crossover to recombine information, so that to generate an offspring which is expected to receive an even higher evaluation. In order to prevent to have a local solution, a mutation which is a genetic procedure to create a new individual is processed probabilistically. A series of selections, crossovers, and mutations is deemed as an operation on a single generation. By repeating the operations on some generations, the population should be evolved gradually into a population having a higher evaluation as a whole.

C. *The problems in finding the optimum in Kansei landscape*

In III-A, a Kansei model has been explained using an example of T-shirt. In this example, the neighborhood on a space is easily defined, since only two parameters are dealt; a color and a pattern. However, the number of parameters an item has is generally large. When the words in the description of goods are set as design variables, the number of parameters would be relatively large. Especially books which are the subject of this research contain so many words in their descriptions, so that the number of parameters would be gigantic. It is unrealistic to deal with the dimensions of all the parameters, so that the numbers of dimensions must be reduced. At the same time, it is necessary to define how the genetic procedures should be processed when iGA is applied in a space with reduced dimensions.

IV. THE PROPOSED SYSTEM

A. *Overview*

In this chapter, a recommender system applying iGA is proposed. The object of this system is to recommend an item according to user's Kansei by forecasting user's Kansei parameters using iGA

The procedures of the proposed method are described as the following;

1) Taking an item apart into words to be feature vectors.
2) Generating multiple candidates of Kansei parameters from user's past behavior.
3) Presenting the items similar to the generated candidates of Kansei parameters.
4) Repeating the procedure 2 and 3 above.

Procedure 1 is the data processing phase which is processed prior to the system implementation, and procedure 2 and 3 are the optimizing phase in which a user and the system interact with one another. In the data processing phase, the system presents only the titles and the pictures of recommending items to a user, so it is difficult to have a user evaluate these items without browsing detailed information of the presented items. From this reason, in the proposed method, the item which the user transited and browsed among the presented titles is evaluated under the genetic algorithm

As many preceding studies have done, the words in descriptions attached to the item are used as the definitions of feature vectors, and TF-IDF weighting scheme [4], [18] is applied as the method of weighting.

In this study, the combination of feature vectors and parameters are accounted as the candidates of user's Kansei parameters. Since words appeared in the description would be enormous, it is expected to impact adversely on solution searches. In order to improve the efficiency of solution searches, it has been studied to convert enormous design variables into a manageable form. For example, a method uses Principle Component Analysis (PCA), and maps design variables onto other principal components, so that the numbers of dimensions can be reduced [19]. Another method is to learn user's preference prospectively as the initial individual is generated, so that the convergence of individuals can be accelerated [20]. In this study, a method is used in which the relevance, different from weighting, between design variables is defined so as to perform genetic procedures on design variables on different dimensions. Using this method, there is no need to store all the design variables as genes. Then, a contents parameter network is constructed in which the relationship among words in contents is expressed by numerical numbers, and the combination of these numbers and parameters are the object of the optimization.

B. *Content Parameter Network*

The graph which expresses the relationship among words in this study is called a content parameter network. In a content parameter network, it is required to define the relationship among words, reflecting the distance among words as people feel it is natural. In this study, feature words are selected from document data such as descriptions attached to an item, using TF-IDF weighting scheme. After the selection, a contents parameter network is constructed based on co-occurrence probability of feature words. If all the co-occurrence probability is adopted as edges, the number of edges is exponentially increased. Thus, it is required to apply a restriction, such as only the edges having high relevance are adopted. As an example, the contents parameter networks regarding the word of "Pattern Recognition" and "fNIRS (functional Near-Infrared Spectroscopy)" are shown in Fig. 3.

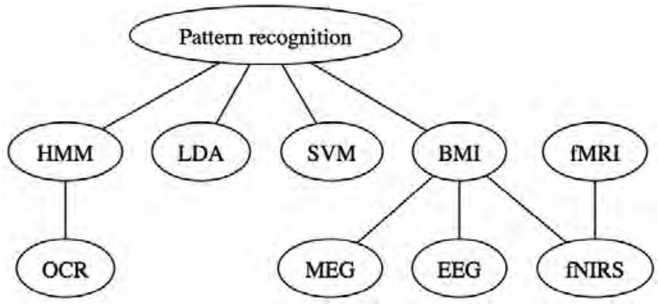

Fig. 3 An example of a contents parameter network

In the example, 'SVM (Support Vector Machine)' and 'fNIRS' have a distance in terms of the meaning of the words and their attribution, but fNIRS is sometimes applied as one of the pattern recognition techniques in 'BMI', so that there should be the relevance. Some of the systems of vocabulary which express the relationships among words, such as thesaurus, are open to the public for academic use. Also, various methods that automatically construct the relationships among words are proposed [21]-[23].

C. The Genetic Procedures of iGA on Content Parameter Network.

Since the neighborhood of candidate solutions is defined as content parameter network, the special crossover method which is fit to this expression is prepared. An example of crossover is shown in Fig.4.

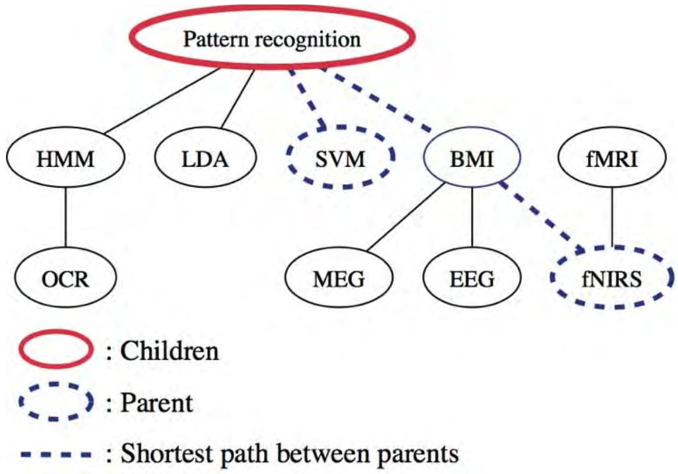

Fig. 4 An example of crossover

At the crossover of the parent words; 'SVM (weighting: 0.4)' and 'fNIRS (weighting: 0.7)', the shortest route of these two words is to be searched on the contents parameter network. In this example, a route starting from 'SVM' followed by 'Pattern recognition' and 'BMI' toward 'fNIRS' is chosen as the shortest route. Then, the node of the offspring is selected from the individual words on the route by a roulette selection. In order to the weightings of the parent individuals are to be linear, the probability of selection is allocated to all the nodes on the route. In this case, the probability of selection is allocated to each of the words as the following; SVM (0.4), Pattern recognition (0.5),

BMI (0.6) and fNIRS (0.7). Then, one of these words is selected as a gene of offspring individual based on the probability. A mutation procedure is a process that transforms a node into another node among Kansei parameters. Adding mutation procedures, it can prevent the deviation of the search area, and rather widen the search area to other area, so that a user might get an awareness of a new item.

V. The Experiment On System Evaluation

A. The Object of the Experiment

The object of the experience is to examine if the proposed system learns the user's preference from his/her past behavior, and recommends the contents having similar key words. The experiment utilized the merchandise data at Rakuten-Ichiba, hereinafter called e-commerce data. The details of e-commerce data is shown in Table. I. Only the book data from e-commerce data is the subject of this experiment. Because this e-commerce data is from Japan, all the data is in Japanese and words are translated into English by authors.

TABLE I. THE DETAILS OF E-COMMERCE DATA

The number of merchandises registered	60,123,534
The number of book data registered	3,555,750
The descriptive items on a Merchandise	Merchandise code, price, description, description according to selling methods, merchandise URL, number of reviews, the average of reviews, merchandise image URL, store code, genre ID, registration date

B. *Outline of experiments*

Two kinds of experiments were conducted; one was the data processing experiment in which the contents parameter network was constructed. This experiment was carried out during the construction of this system. Another was the experiment with subjects so that the tendency of recommending contents could be examined. The details of each experiment are explained as following:

1) Data Processing Experiment

In the data processing experiment, data was processed using the following items; name of merchandise, description of merchandise, description according to selling methods and genre ID out of description data attached to merchandise. Using genre ID, the whole datawas narrowing into only book data. Then, the system selected feature words using TF-IDF weighting scheme, and constructed a contents parameter network based on co-occurrence probability of feature words, as described in IV-B. A restriction was applied on generating edges of a network; only two of the edges having the highest relevance at each of the node were adopted as the edges of a network. This restriction was to prevent from interconnecting all the nodes because of the excess of edges.

2) The Subject Experiment

In the experiment with subjects, two methods were compared; one was the method which was applied the assumption of the user's parameters through the proposed system. Another was the method in which only the main key words of the item were adopted as the feature values. Fig.5 shows the he interface used in this experiment.

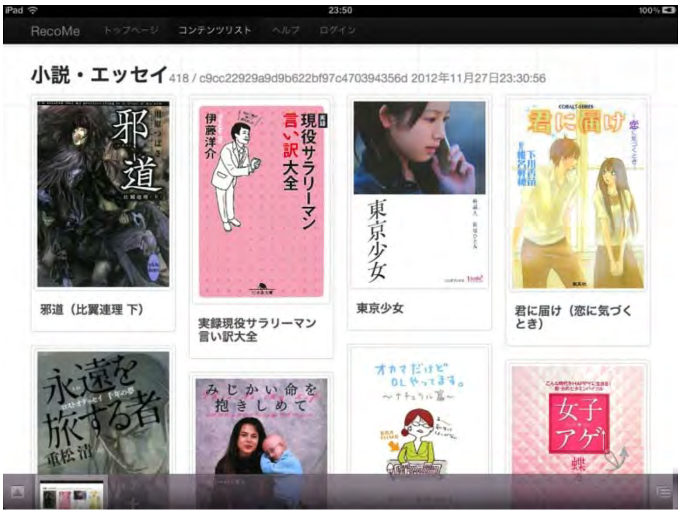

Fig. 5 The interface used in this experiment (showing the initial individuals)

On the screen of tablet PCs, multiple titles and images of books were presented, and the subjects were instructed to find the items he/she was interested and touch the image of the book to select. This selection information is selected and new candidates are shown in the next screen. The subjects were the total of six people, combining males and females, and they were aged between 22 and 25. The rate of mutation was 0, and the number of generations was 5. The number of Kansei parameters used in learning was 10, and the number of merchandises shown on the screen at a time was 8. These parameters had been determined by the preliminary experiment.

VI. THE RESULT

A. *Data Processing Experiment*

E-commerce data has been analyzed and the results are shown in Table. II. The overview of the contents parameter network generated in this experiment is shown in Fig. 6.

TABLE II. THE DETAILS OF THE ANALYZED DATA

Data	Number
Book data registered	3,555,750
Nodes of network	221,970
Edges of network	437,704

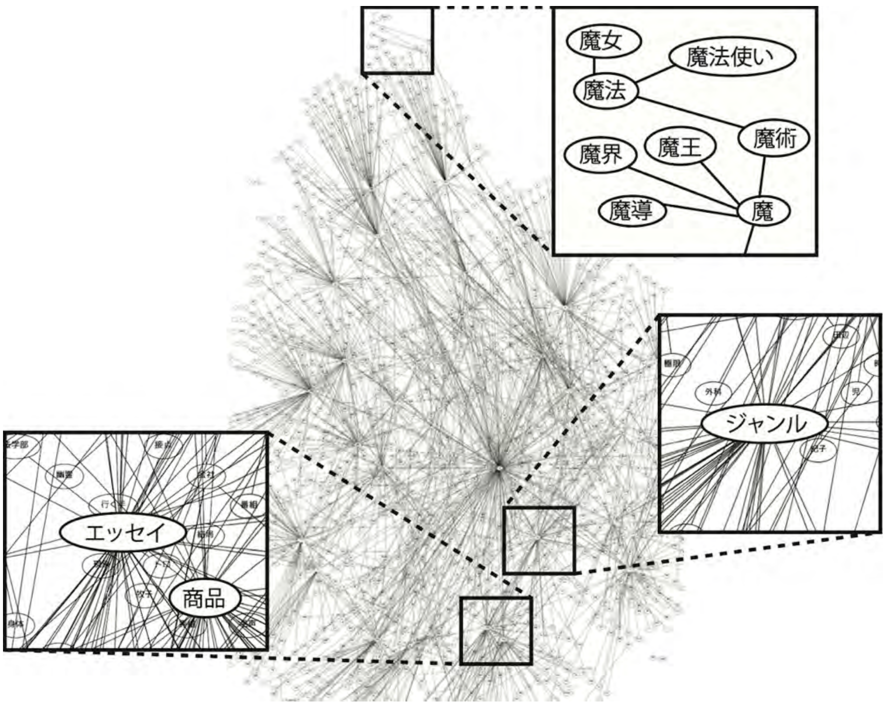

Fig. 6 The overview of the contents parameter network generated in this experiment

As one of the characteristics of the contents parameter network generated in this experiment, it is observed that specialized words, such as ‘magic’ and ‘wizards’ which are likely to be main themes of fantasy novels, have been interconnected at the end of the network. In contrast, the words such as ‘novels’, ‘genres’, and ‘essays’ are appeared at the center of the network. These words are generally placed higher rank on thesauruses compared to the words at the end of the network. The center of the network is a hub of the network, and the many branches are coming out of the hub. From the results described above, it is determined that the specialized words are interconnected on the contents parameter network through their higher concepts.

B. The Subject Experiment

The browsing history of images, the titles and the authors of the books a subject selected are shown in Fig. 7. Also, the catalog of the recommendations by the proposed method is shown in Fig. 8. The examples of Kansei model assumed in the experiment are shown in Table. III. The example of the contents parameter network which is used on the crossover during the assumption of Kansei model is shown in Fig. 9.

Fig. 7 The history of the books a subject selected

Fig.8 The catalog of the recommended books by the proposed method (the final generation)

TABLE III. THE EXAMPLES OF KANSEI MODEL ASSUMED

Generation	Kansei model assumed: sorted (weighting)
1	Novel (0.61), novel (0.56), novel (0.30), novel (0.24), Sasaki (0.22), department (0.19), gt(0.15), Murakami (0.14), underground(0.11), novel (0.10)
2	Library (0.59), Maki (0.54), novel (0.34), moon (0.26), time (0.22), gt(0.19), moon (0.14), novel (0.13), information (0.11), merchandise (0.11)
3	Haruki (0.61), novel (0.56), Haruki (0.31), gt(0.24), cmISBN(0.21), moon (0.17), gt(0.14), hardcover (0.14), nbsp(0.11), moon (0.10)
4	Essay (0.64), author (0.45), time (0.30), department (0.27), room (0.25), novel (0.21), writing (0.18), novel (0.14), merchandise (0.12), novel (0.12)

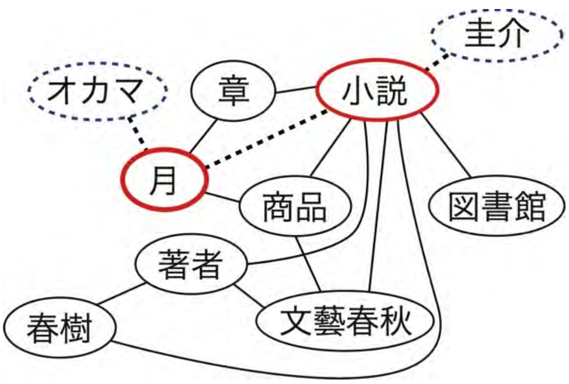

Fig. 9 The example of the contents parameter network used on the crossover

This subject selected a book called “A Reference to Gentlemen” as her second generation. The words shown in the network are the name of the author and key words of title. Using these words, the proposed system conducted acrossover on these words. As the result, the new key words

are derived. These words lead to the book called “Sputnik Sweetheart” written by Haruki Murakami was recommended by the system. Selecting the book recommended above, a tendency was observed that books written by Haruki Murakami and essays, rather than novels, were recommended.

VII. DISCUSSIONS

Through the experiments, it was observed that the recommendations had been differed by embedding the learning system of Kansei parameters. In this chapter, the generation of Kansei parameter which is the main reason of this difference is considered. In the proposed method, learning is defined as the following; the key word which belongs to the item being currently browsed and another key word which has been presumed as Kansei model are interconnected on the conceptual word network. Then, the next generation of Kansei model is transferred to one of the words on the shortest route between two words. When the crossover is processed on different words in the proposed system, the shortest route between two words is chosen, and a roulette selection is performed. Thus, the feature words which conceptually interconnect different items are generated. In this experiment, the feature words such as ‘novel’, ‘essay’ and ‘moon’, were generated, although these words belong to neither of the parent individuals. Then, the recommendation was made based on the generated information.

VIII. THE CONCLUSION

In order to make recommendations based on human’s Kansei, the recommender system using interactive genetic algorithm is proposed in this paper. Applying the contents parameter network as the definition of neighborhood, the proposed system is able to process the crossover between the words on different dimensions. Applying this method to merchandise data from an online shopping site, it was observed that the items considering user’s past selections were very likely to be recommended by the proposed system. The proposed method should be able to recommend an item using the concept which is newly generated from the feature values of parent individuals, so that the recommended item should have the various and instinctive connection with users’ preferences. Moreover, this method is expected to be applied and implemented not only to merchandise recommender systems, but also to other recommender systems such as recommender system for academic theses; the system would present some examples from the area of study which a user is interested in but not familiar with, and the presented examples would be similar methods, problem solving approaches, and so on.

REFERENCES

[1] A. Das, M. Datar, A. Garg, and S. Rajaram, “Google news personalization: scalable online collaborative filtering,” in Proceedings of the 16th IEEE, 2007, pp. 271–280.

[2] G. Linden, B. Smith, and J. York, “Amazon.com recommendations: item-to-item collaborative filtering,” in Internet Computing, IEEE, vol. 7, 2003, pp. 76–80.

[3] J. Herlocker, J. Konstan, and J. Riedl, “Explaining collaborative filtering recommendations,” in Proceedings of the 2000 ACM conference on Computer supported cooperative work, 2000, pp. 241–250.

[4] M. J. Pazzani and D. Billsus, “Content-Based Recommendation Systems,” in The Adaptive Web, Springer Berlin Heidelberg, 2007, pp. 325–341.

[5] M. Balabanovic, “Exploring versus exploiting when learning user models for text recommendation,” in User Modeling and User-Adapted Interaction, vol. 8, 1998, pp. 71–102.

[6] H. Takagi, T. Unemi, T. Terada, “interactive Evolutionary Computation, ” Snagyo-Tosho, Tokyo, 2000, pp. 325–361.

[7] B. Sheth and P. Maes, “Evolving agents for personalized information filtering”, in Proceedings of the 1993 Artificial Intelligence for Applications on Ninth Conference, 1993, pp. 345–352.

[8] M. Atsumi, “Extraction of User’s Interests from Web Pages based on Genetic Algorithm”, in Proceedings of Information Processing Society of Japan, The Special Interest Groups Notes, 1997, pp. 13–18.

[9] Y. Cao and Y. Li, “An intelligent fuzzy-based recommendation system for consumer electronic products”, in Expert Systems with Applications, vol. 33, 2007, pp. 230–240.

[10] A. Goy, L. Ardissono, and G. Petrone, “Personalization in e-commerce applications”, in The Adaptive Web, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007, pp. 485–520.

[11] Y. Zhang and J. Koren, “Efficient bayesian hierarchical user modeling for recommendation system”, in Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval, 2007, pp. 47–54.

[12] I. Zukerman and D. W. Albrecht, “Predictive Statistical Models for User Modeling”, in User Modeling and User-Adapted Interaction, 2001, pp. 5–18.

[13] H. Takagi, K. Aoki, and N. Fujimura, “Interactive GA-based Design Support System for Lighting Design in Computer Graphics”, in Intenational Conference on Soft Computing, 1996, pp. 533–536.

[14] M. OhsakiH. Takagi, “Improvement of Presenting Interface by Predicting the Evaluation Order to Reduce the Burden of Human Interactive EC Operations”, in IEEE International Conference on System, Man, Cybernetics, 1998, pp. 1284–1289.

[15] H. S. Kim and S. B. Cho, “Application of interactive genetic algorithm to fashion design”, in Engineering Applications of Artificial Intelligence, vol. 13, 2000, pp. 635–644.

[16] S. B. Cho, “Towards Creative Evolutionary Systems with Interactive Genetic Algorithm”, in Applied Intelligence, vol. 16, 2002, pp. 129–138.

[17] M. Sugahara, M. Miki, and T. Hiroyasu, “Design of Japanese Kimono using Interactive Genetic Algorithm”, in IEEE International Conference on Systems, Man and Cybernetics, 2008, pp. 185–190.

[18] G. Salton, A. Wong, and C. S. Yang, “A vector space model for automatic indexing”, in Commun. ACM, vol. 18, 1975, pp. 613–620.

[19] M. Tanaka, T. Hiroyasu, M. Miki, S. Yasunari, and M. Yoshimi, “Automatic Generation Method to derive for the design variable spaces for interactive Genetic Algorithms”, in IEEE World Congress on Computational Intelligence, 2010, pp. 1256– 1263.

[20] A. Amamiya, M. Miki, and T. Hiroyasu, “Interactive Genetic Algorithm using Initial Individuals Produced by Support Vector Machine”, in The Science and Engineering Review of Doshisha University, vol. 50, 2009, pp. 34–45.

[21] H. Fujii, Atsushi and Tokunaga, Takenobu and Tanaka, “A Hybrid Approach for Measuring Word Similarity”, in IEICE technical report. Natural language understanding and models of communication, vol. 97, 1997, pp. 53–58.

[22] H. Watabe, N. Okumura, T. Kawaoka, “The Method of Measuring the Degree of Association between Concepts using Attributes of the Concepts and Coincidence Information”, Natural Language Processing, vol. 13, 2005, pp. 53–74.

[23] M. Kato, H. Ohshima, S. Oyama, “Bootstrap extraction of similar relations from the web by term co-occurrences”, The *Database Society* of Japan Journal, vol. 8, 2009, pp. 11–16.

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