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# CBCRS: An open case-based color recommendation system

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## A B S T R A C T

In this paper, a case-based color recommendation system (CBCRS) is proposed for online color ranges (CRs) recommendation. This system can help designers and consumers to obtain the most appropriate CR of consumer-products (e.g., garments, cars, architecture, furniture ...) based on the color image perceptual data of each specific user. The proposed system is an open system, permitting to dynamically integrate new CRs by progressively learning from users' and designers' perceptual data. For this purpose, a Color Image Space (CIS) is initially established by using Basic Color Sensory Attributes (BCSAs) to obtain the color image perceptual data of both designers and consumers. Emotional Color Image Words (CIWs) representing CRs are measured in the proposed CIS through a knowledge-based Kansei evaluation process performed by designers using fuzzy aggregation operators and fuzzy similarity measurement tools. Using this method, new CIWs and related CRs from open resources (such as new color trends) can be integrated into the system. In a new recommendation, user's color image perceptual data measured in the proposed CIS regarding different BCSAs will be compared with those of CIWs previously defined in the system in order to recommend new CRs. CBCRS is an adaptive system, i.e. satisfied CRs will be further retained in a Successful Cases Database (SCD) so as to adapt recommended CRs to new consumers, who have similar user profiles. The general working process of the proposed system is based on case-based learning. Through repeated interactions with the proposed system by performing the cycle of *Recommendation – Display – Evaluation – SCD adjustment*, users (consumer or designer) will obtain satisfied CRs. Meanwhile, the quality of the SCD can be improved by integrating new recommendation cases. The proposed recommendation system is capable of dynamically generating new CIWs, CRs and new cases based on open resources.

### Keywords:

Color recommendation  
Dynamical system  
Case-based learning  
Collaborative system  
Design evaluation  
Human perception

## 1. Introduction

Strongly related to the appearance of consumer-products [30], color is one of the major attributes that affect consumer perception of a product image [12]. Normally, in the process of color design, several single-color combinations, known as color range (Fig. 1-b), will be determined by designers. The color range (CR) of a product plays important roles in beautifying the product, improving the competitiveness and satisfaction grade of the good, and enhancing the efficiency of the designer's work [30]. As the most visually impactful part of a product, color has a direct impression on consumers, which makes it one of the key elements determining the value property of a product [9]. Recently, consumers' personalized demands on consumer-products are increasing, which raises

the importance of color in both artistic activities and daily life [14,20,34]. Both designers and consumers require a fast and efficient color recommendation method.

In response to the increasing demands about personalization of consumer-products, color trends are created and promoted to both designers and consumers, especially in the fashion industry. An explosion of color trends is occurring at an unprecedented rate. A color trend is normally defined as a "trendy" color image word (CIW) together with its related CR (see Fig. 1-b). CIWs describe the color symbolism of expected CRs. Generally, both designers and consumers are concerned by color trends. Color trends are created over time from the open resources, such as color research institutes, color trend forecast agencies, fashion blogs, social networks. In industry, these color trends should be quickly received and applied to color designs/recommendations, which will shorten product life cycles and win more market share [8]. Color recommendations are decision-making problems in an open resource.

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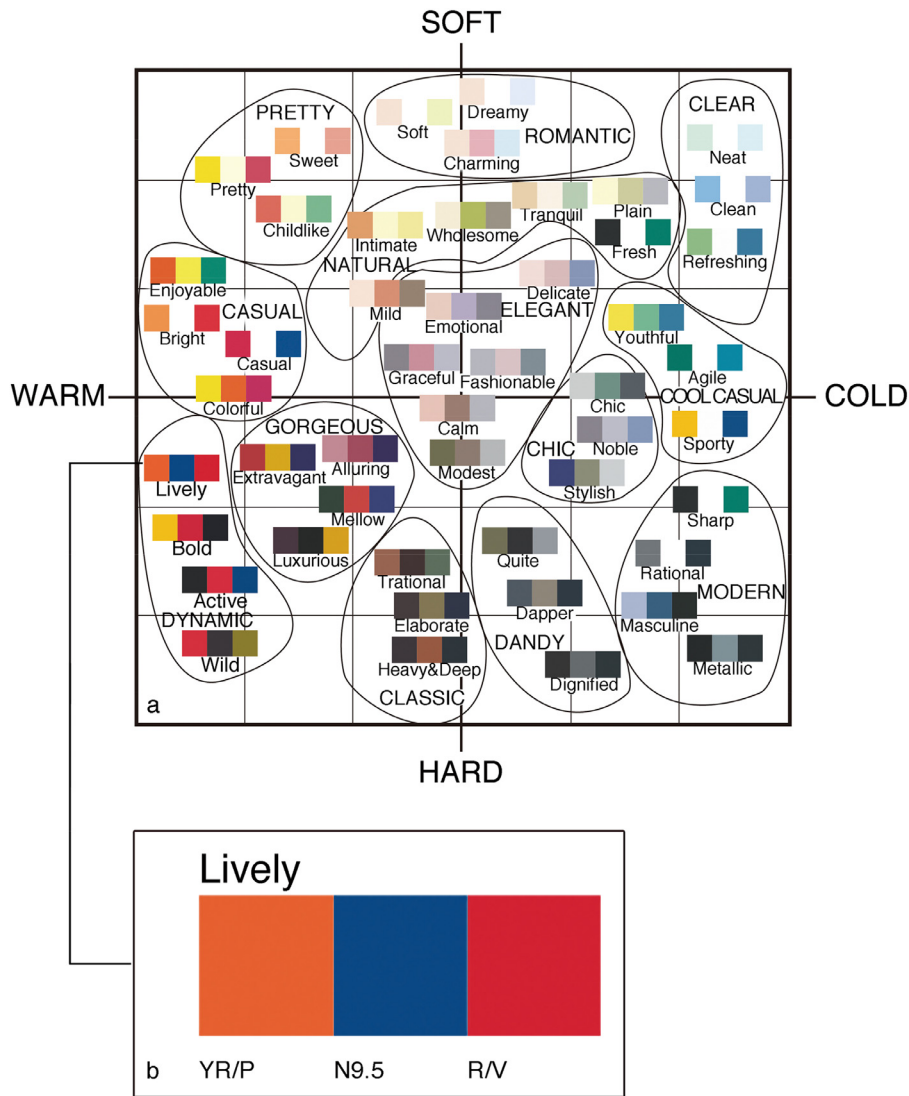


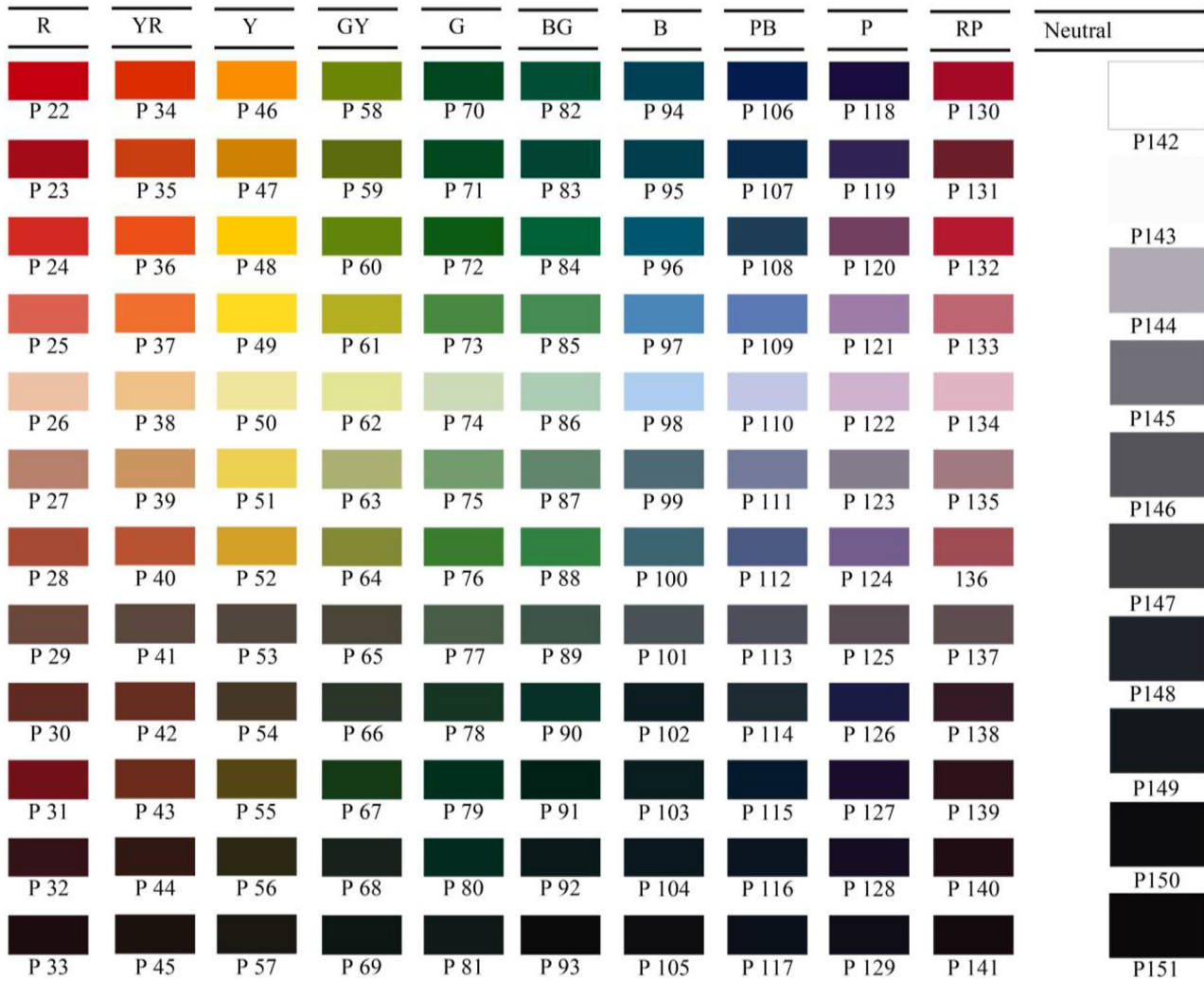
Fig. 1. Color Image Scale developed by Kobayashi: (a) 180 CIWs, their corresponding CRs and measurements in a 2D CIS; (b) CRs, their descriptive CIWs and physical color properties. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The success of color recommendations also relies on the consumer's preference (color image perception). However, consumer's preferences are dynamically changing over time because their preferences are relative to their mood and the socio-culture environment. Color recommendations deal with both consumer's color image perceptual data and color trend data, which are dynamical and quickly vary with time and socio-culture. Since data concerned by color recommendation is diversified, and massive, color recommendation is also a decision-making problem in a scalable data environment.

Traditionally, in the process of personalized product design and development (PD&D), a recommendation of an appropriate CR, starts by offering the consumer a few CIWs of expected finished products [36]. Then, the consumer's color image perception represented by the CIWs will be analyzed by designers using their experience and referring to the current color trends [4]. After several interactions between the consumer and designer, the final optimized CR can be determined, based on the knowledge and experience of the involved designers [35]. This CR will be further applied to determine the final visual presentation of the desired product. However, it is impossible for designers to receive and apply all the latest color trend information. The traditional method is insuffi-

cient in the management of color data in large scale obtained from the open resource. The traditional method is strongly related to the professional level of the designers, which is not only time consuming but also cannot ensure a stable accuracy of the color recommendation results. Color recommendation, as a decision-making problem in a scalable data environment, cannot be handled by the traditional method.

In order to solve this problem, different researchers developed some color recommendation systems. Meier proposed a color design system for automatic CR generation based on a number of identified color rules [37]. Cohen developed an automatic recolor method for a given color palette by using an optimized process of human-machine interactions [10]. Also, there are some color recommendation systems, using the results of color image perception. In these systems, products with single color and CRs are evaluated and formalized by CIWs using fuzzy set theory and Kansei engineering-based expert system. Color image perception studies provide new solutions for color recommendation. For example, the Color Image Scale is a study on color image perception established by Kobayashi [22]. In the Color Image Scale, 180 CIWs related to emotions, lifestyles, and tastes are selected to describe over 2000 CRs (see Fig. 1-a). The form of using CIWs describing CRs is also



**Fig. 2.** 130 Colors used in this research include 120 chromatic colors and 10 achromatic colors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

used in the description of standard color trends. These CRs are determined by 130 basic colors, including 120 chromatic colors and 10 achromatic colors (see Fig. 2). A group of designers was involved in the investigation of the relationship between CIWs and CRs. As a definitive color resource used by designers and manufacturers from different countries, the Color Image Scale is a widely used systematic database that has proved to be mature and reliable.

Moreover, based on the research results of the Color Image Scale, Ana [28] developed a personalized recommendation system using a color image-based image retrieval and ranking method. Her research enables to decompose the image to be retrieved into CR using the 130 basic colors of Kobayashi. CRs of images in the database will be matched with the CRs of Kobayashi's database. Then each image to be retrieved will permit to generate a CIW, which is taken from the 180 CIWs of Kobayashi. When a user gives a CIW, the corresponding CR and its associated relevant images will be recommended. This approach is strongly related to the research results of the Color Image Scale. However, in the Color Image Scale, color image perception of the involved 180 CIWs is measured in a 2D CIS (Abscissa: Soft–Hard, Ordinate: Warm–Cold), meaning that it is not sufficient to measure the rich emotions of the color image perception of human beings [22]. Also, Ana's system is static and stationary, which is impossible to process dissatisfactions of a user.

Ladys [27] developed a similar color image perception-based color recommendation system with an improved system structure design. This system utilizes the designer's knowledge and experience to extract design rules and process the relationship between CIW and CR. These rules enable to guide the search for customer's preferences and uses contextual information to model the customer's fitness function. Based on an interactive genetic algorithm and an ANN model, the related CR can be predicted from the user's color image perception. This system has been designed with a feedback mechanism, in which the dissatisfaction of a user can be efficiently processed. However, there are always exist differences between designers and consumers on the understanding and the description of color symbolism when using CIWs. These perceptual differences are caused by the cross-cultural background and linguistic gaps of involved designers and consumers [25]. The understanding of user's color image perceptual data is rather weak.

In a current color recommendation, related color design rules are very limited and easily influenced by the cross-cultural backgrounds of involved designers and consumers. This problem concerns by all designers. Another issue in a current color recommendation system is that it is incapable of dynamically processing color recommendation-related information. The way the user's perception of the latest color trends evolves cannot be quickly integrated into the systems [28,27]. For solving these problems, a

dynamical color recommendation process, capable of dealing with perceptual data of the user's time-varying color images without being affected by cross-cultural factors, and processing the latest color trend information, is strongly required by both designers and consumers.

It can be found that, in general, color recommendation systems have a number of special features, which are quite different from the most of consumer-oriented recommendation systems, e.g. tourist route and food recommendations. More oriented to professional users, they usually aim at proposing the most relevant color ranges to product designers by establishing a reliable relationship between color parameters (product technical space) and human perception and emotions (fashion design space). With recommended color ranges (CRs), designers can easily find relevant solutions for designing consumer products adapted to their desired fashion themes and aesthetic requirements. The existing color recommendation systems in the literature [28,27] generally follow this principle. They utilize the designer's knowledge and experience to extract design rules and relations between CIW and CR for guiding the search for customer's preferences and model the customer's fitness function from contextual information. Based on different learning algorithms such as ANN and ANFIS, a relevant CR can be predicted from the user's color image perception. These systems have been usually designed with a feedback mechanism, in which dissatisfaction of users on recommended CRs can be processed in order to obtain desired recommendation results.

However, in practice, identification of a reliable relationship between technical parameters and human perception/emotions is rather difficult due to the existence of uncertain factors in human perception (culture, personality, education, religion, ...). Concretely, there are several limits in the existing color recommendation systems: (1) automatic understanding capacity of color image perception/emotions of a user is rather weak, (2) knowledge-based design rules, i.e. reliable relations between technical parameters and human perception/emotions are uncertain and very limited, and (3) these systems are static, and unable to deal with user's time-varying color images perception/emotions affected by the latest color trend information.

Based on the existing work [28,27], we propose a knowledge-based color recommendation system that can recommend the most appropriate CR for industrial products. The proposed system obeys the same principle of the existing color recommendation systems. It is a knowledge-based system and integrates a feedback mechanism in order to progressively improve recommended results through user-computer interactions. A new multidimensional CIS will be defined in the proposed system. CIWs and CRs of Kobayashi's Color Image Scale will be re-characterized in the proposed CIS. These CIWs and CRs will be applied as the initial database of the proposed color recommendation system. Further, referring to color trends, these CIWs and the CRs of the proposed system will be updated. The proposed system is an open system, which is capable of dynamically dealing with user's color image perceptual data and integrating the latest color trends [26]. Color design rules are extracted by designers using their professional knowledge through a series of human evaluation experiments [7]. Using these rules, CIWs developed by Kobayashi [21] can be identified in a novel multidimensional CIS defined by a set of Basic Color Sensory Attributes (BCSAs). In the same way, color trends (CIWs and their related CRs) from an open resource will be evaluated by designers and integrated into the proposed system. BCSAs applied in this research are carefully selected for easy understanding by consumers. For example, "Warm-Cold", can actually avoid semantic confusion. Also, the recommendation process is based on case-based learning, realized by similarity measurement [2]. Successful recommendation cases of the proposed system are stored in a predefined Successful Cases Database (SCD) [32]. This SCD

includes user's sociocultural data (gender, religion and education background and other cross-cultural background factors), color image perceptual data measured in the CIS regarding BCSAs and satisfactory color recommendation results. The data of a new consumer will be compared with the SCD in order to find the most similar case. The corresponding CR of this case will be reused by the system as a recommendation result. Through interactions with the consumer on the evaluation of satisfied and unsatisfied attributes of the recommended CR, a feedback mechanism is established for generating new recommendations. New design cases will be retained in the proposed SCD in order to increase the accuracy of the recommendations.

The novelties of the color recommendation system with case-based learning include the following aspects: (1) Compared with the current research results, the input of the consumer is simplified by using a set of BCSAs that are easily recognized by non-specialists without professional knowledge. (2) A multidimensional CIS is established to provide more possibilities for expressing the rich emotions and perceptions of human beings. (3) The proposed algorithm is based on case-based learning, which can solve the problem caused by cross-cultural factors in the color recommendation. (4) The proposed system is an open resource-based system, capable of progressively integrating new recommendation rules (new CIWs and related CRs) from successful applications for improving the quality of coming recommendations.

Velocity and variety characteristics of the color trends are the most important features of data studied in this research. These data include: (1) consumer's color image perceptual data, and (2) color trend data. In practice, both of them quickly vary with time and socio-cultural evolution. Compared with human evaluation data in other fields, classical color data analysis is more limited to a given specific fashion area and time period and then the obtained results cannot be significant in a general sense. In this context, data analysis approaches with open source will permit to be quickly adapted to all kinds of fashion situations in terms of personality, society, culture and time. Even though the data size may be small at the initial stage when the system starts to offer the service to users, it will be progressively increased for covering all possible scenarios.

The proposed color recommendation system can effectively help young and inexperienced designers or even amateurs in their product design processes. The general idea of this paper has been presented to different fashion designers and widely accepted by them. The positive responses from fashion industry permits to effectively validate the proposed system.

The rest of the paper is structured as follows. In Section 2, the overall scheme and related methods of the proposed recommendation system are provided. In Section 3, two experiments are presented for setting up the proposed system. Section 4 presents different case implementations to explain the working process of the proposed system. Section 5 discusses the related data and investigates how knowledge exploitation and case-based learning support the proposed system. Finally, a conclusion is provided in Section 6.

## 2. Methodology

In this study, design knowledge on the color image perception is extracted to support the recommendation process. To extract this design knowledge, a set of BCSAs (non-emotional basic color sensory attributes) should be first established. Then, through a series of Kansei-based human evaluation performed by a group of designers, the perceived relations of the 180 CIWs (emotional color image words) used in the proposed system regarding BCSAs are identified. These identified relations are taken as the design rules, which will be used in the recommendation process. The Design-

ers' Color Design Knowledge Base (DCDKB) is represented by these rules.

In the recommendation process, the users' color image perception will be analyzed in a novel CIS (Color Image Space). The system will retrieve the CIW which has the most similar color image perception with that of this specific user. The design rules characterizing the relations between the 180 CIWs and BCSAs of the CIS will be used in this process, which is supported by the designer's knowledge and experience.

The user's evaluation on the recommended color range will be performed regarding the basic color physical properties (*hue, lightness, and purity*). According to the evaluation results, these color parameters can be further modified or defined to generate new recommendation. When a recommended CR is satisfied by the consumer, the consumer profile (sociocultural background data such as *gender, education background, religion...*), the color image perception data and the related color recommendations of this user will be retained in the SCD for further recommendations to users with similar consumer profiles.

### 2.1. Principle of the proposed system

The proposed methodology for human evaluation in this approach is based on Kansei engineering (emotional/affective engineering), which aims at developing or improving products and services by translating the customer's psychological feelings and needs on products to be designed [18,38]. Kansei engineering parametrically links the customer's emotional responses to the properties and characteristics of a product or service. In consequence, products can be designed to bring forward the intended feeling.

In the proposed recommendation system, by following the principle of Kansei engineering, both designers and consumers will evaluate their color image perception using a set of BCSAs (Basic Color Sensory Attributes) of a novel color image space (CIS). Also, designers will evaluate the color image perception of CIWs (color image words) while consumers will evaluate their subjective color image perceptions of the desired product. Using this method, the CIWs corresponding to the color images desired by a specific consumer can be identified. Further, the associated color range of the identified CIWs will be recommended to the consumer.

There are two knowledge bases used in the proposed recommendation system, namely (1) Successful Case Database (knowledge container for past successful specific cases), and (2) DCDKB (knowledge container for designers' general color design knowledge). These two kinds of knowledge constitute two different ways of recommendation of the proposed system.

When a new user uses the proposed color recommendation system, he/she needs to input the following required information: personal profile and color image perception data. These two parts constitute the retrieved new case for being compared with the existing cases in the SCD in order to find the most relevant case according to a predefined similarity degree.

If there are one or more existing cases in the SCD, whose similarity degree compared with the retrieved new case is higher than a predefined threshold, a case-based recommendation will be performed. The retrieved case which has the highest similarity degree is then considered as the target case, and it will be reused for recommendations. In the real application, the threshold is defined by specific users of the system according to their personalized perceptions. In this study, for simplifying the problem, the threshold is set to be 85%. The corresponding CR of the target case will be presented as recommendation result to the new user. If the user is satisfied with this result, the recommendation process will stop. If there is no target case in the SCD meeting the required threshold or the new user is not satisfied with the recommended color of the target case, the corresponding color design rules or

knowledge will be updated. In the real recommendation procedure, what usually occurs is that there are one or more cases in the SCD which have the same similarity degrees related to the target query case. In this situation, the case in the SCD having the highest successful recommendation frequency will be recommended.

If there is no case meeting the similarity degree in the SCD, a designer's knowledge-based recommendation process will be performed. The color perceptual data regarding BCSAs of the user will be compared with CIWs in the Color Range Database. The CR of the CIW which has the highest similarity degree will be recommended to the consumer. Similarly, if the user is not satisfied with the recommendation, he/she is requested to give feedback to the system, and the system will generate new recommendations based on this feedback until the final result satisfies the user.

The color design knowledge updating process starts by computing the similarity degree of the color image perception of the new user related to the color image perception of the CIWs initially identified by designers. The most similar CIW and its corresponding CR will be provided as a new recommendation. Initially, these CRs are taken from a Color Range Database, developed from the research result of Kobayashi (See Fig. 1). If the user is satisfied with the new recommendation, the process will stop. Otherwise, the user will be requested to provide a comment on the recommended CR in terms of lightness, purity, and hue, or choose a color directly from the color database shown in Fig. 2. Users are free to add or delete colors based on the recommended CR. This process is based on the basic parameters of color and can be easily understood and performed by the user. Referring to the latest color trends, the proposed Color Range Database can be updated with new CRs and their descriptive CIWs through a knowledge-based human evaluation process performed by the designers.

The procedure of *Recommendation – Display – Evaluation – SCD adjustment* will be performed by the user several times until a satisfactory result is obtained. After the acceptance of a recommended result, it will be retained in the SCD as a new case-based learning rule, enhancing the recommendation accuracy of the proposed system.

When more and more users use the proposed the recommendation system, the color design knowledge bases, namely SCD (successful specific case database) and DCDKB (designers' general color design knowledge) will be progressively enhanced. Especially, the design rules extracted from successfully recommended cases will become more complete. The improvement of the quality of the knowledge base can effectively increase the rate of success of the recommendation system.

### 2.2. Related concepts and tools of the proposed system

The proposed case-based machine-learning recommendation system includes four main modules: retrieve, reuse, adaption and retain. A set of knowledge-based design rules, similarity measurements rules and a database are applied to support these modules. These rules and the database constitute knowledge containers to support the whole process (see Fig. 3).

#### 2.2.1. CIS and related BCSAs

A novel CIS is defined as a color image perception measurement system for acquisition of human perceptual data for both designers and consumers. Compared with the classical CIS, the proposed multidimensional CIS is capable of expressing rich emotions, ensuring knowledge extraction from designers and perceptual data acquisition from consumers. The proposed CIS comprises several BCSAs that have been chosen from an extensive range used in the related literature. The feature recommendation process has been conducted through interactions with a number of experts. The selected BCSAs are in the form of word pairs, such as "Cold-Warm",

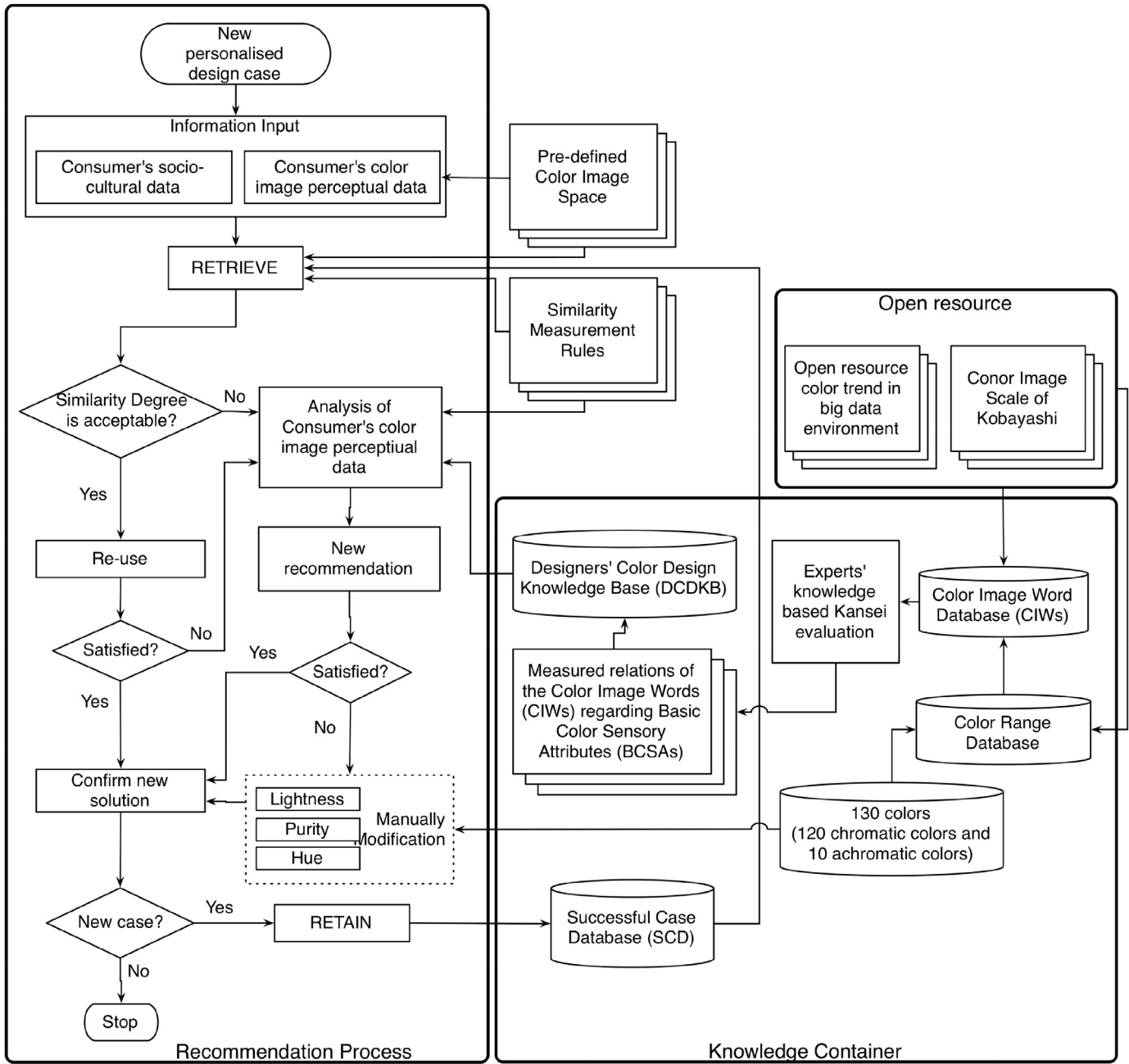


Fig. 3. Working flowchart of the proposed color recommendation system.

that can be easily understood by both designers and consumers without professional design knowledge. More specifically, BCSAs are used to measure the aggregated perceptual data of designers about their color image of CIWs. The relations between BCSAs and CIWs constitute the extracted color design rules of designers, which will be stored in an off-line Designer's Color Design Knowledge Base. The proposed CIS will be used online when a user input his/her color image perceptual data.

### 2.2.2. CIWs and CRs

In this research, a Color Range Database is proposed initially based on CRs developed by Kobayashi. These CRs constitute the recommendation results of the knowledge-based recommendation process. CIWs are applied to describe these CRs. The relationship between CRs and their corresponding descriptive CIWs will be dynamically updated in the recommendation system based on the

feedback of the user. The color image perceptions of CIWs are characterized in the proposed CIS regarding BCSAs by designers, through a human evaluation process. Professional knowledge and experience will be extracted to support this characterization process.

As a dynamical system, the proposed Color Range Database can be updated in two situations. The first one is that, when a consumer is initially not satisfied with the recommendation result and finally obtained a satisfactory recommendation through several interactions with the system, the final modified CRs will be integrated into the Color Range Database. The second one is that, referring to the latest color trend, new CIWs and their related CRs will be integrated into the Color Range Database through a knowledge-based human evaluation process. New CIWs will be characterized in the proposed CISs regarding BCSAs. When a new CIW is applied

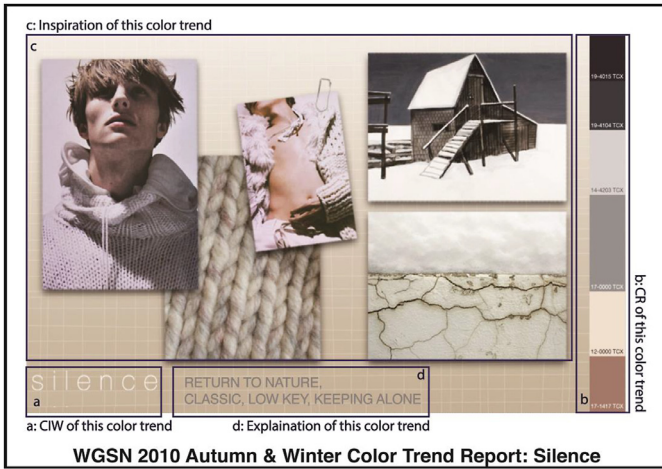


Fig. 4. WGSN color trend report of 2010 autumn and winter. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

by the system, its related CRs will be retained in the proposed Color Range Database.

A CIW may have several different alternative CRs. Each of the CR has a successful recommendation frequency, which indicates how many times this CR has been successfully utilized when this CIW is selected by the system to be recommended to a user (consumer or designer). Alternative CR with highest successful recommendation frequency will be firstly recommended to the user. When new color trends integrated into the system, if there are existing CIW in the system, the corresponding CR will be assigned as one of the alternative CR of this CIW. The Color Range Database (Fig. 3) will be updated. If there is no such CIW in the system, a new CIW will be created in the Color Image Word Database (Fig. 3) and its related CR will be stored in the Color Range Database (Fig. 3) correspondingly. This CR will be defined in the system as NCR, which is different from other existing CRs. These existing CRs are defined in the system as ECR. When a CIW is selected by the system to be recommended to a user, if there exists a NCR for this CIW, this NCR will be recommended to the user and no longer belongs to the group of NCR. It will be regarded as ECR and given a successful recommendation frequency. All the users will be affected by the trends once these trends are integrated into the system. But the existing successful cases in SCD will be not affected. The original BCSA values will not be affected since this is the personal color image perception and they will be stored in the user profile. They will be not affected by any parameters of the system.

### 2.2.3. Color trend

The color trend (known as colors of the year/season), is defined by different color institutes and agencies, such as WGSN, Pantone. Color trends are the forecast for the trendiest color currently and within a short period in the future. To obtain the color trend of each season, color institutes and agencies evaluate the colors shown by different designers in different exhibitions and shows. Among them, the well-known fashion shows in the world, such as New York Fashion Week, Milan Fashion Week, London Fashion Week and Paris Fashion Week, are the most studied ones.

A color trend report is a document presenting the color trend proposed by a color institute or agency. Usually, a color trend report contains four elements: (1) a CIW (Fig. 4a), (2) a CR (Fig. 4b), (3) inspiration for the color trend (Fig. 4-c), and (4) related explanations for the color trend (Fig. 4-d). Fig. 4 presents a color trend report for 2010 autumn and winter, proposed by the WGSN. The inspiration for the color trend is usually presented in several pic-

tures, showing the existing concerned creations and design works. The corresponding explanation is offered by creators of this report, in order to help readers to understand the color trend. Inspiration and explanation are supplementary information of the concerned color trend.

Extraction of a color trend is done by relying on the experience and knowledge of experts (researchers and designers) in these color institutes and agencies. A color trend report is created in the following standard steps: (1) the collections of colors used by designers of the current season, (2) the analysis of the current season's colors by experts, (3) the determination of a CIW for the color trend report, giving several reference pictures for the proposed CIW (inspiration of this color trend), (4) the extraction of CRs based on the inspiration pictures, and most frequently used colors for these inspiration pictures, and (5) giving necessary explanations for this color trend. Normally there will be several experienced experts working on a color trend report. Creating a color trend report is a group decision-making process, and the results of each step in the creating process will be carefully discussed among designers. A step in the creating process can be carried out only when the result of its previous step is approved by all the experts in the decision-making team. Although creating a color trend report is a rather subjective work, the group discussion of different experienced experts can lead to a common result through a standard working process.

In this research, CIWs and their related CRs of color trend reports from the open resource are extracted and applied to the proposed system. Color image perception of a new CIW from a new color trend report will be evaluated regarding BSCAs of the CIS by designers. Through the analysis of designers, color trends from the open resource can be integrated into the Color Range Database. New recommendations can be generated after the integration of a new color trend.

### 2.2.4. Case, success case, and SCD

A case is defined as a representative consumer together with his/her personal profile, color image perception data and related color recommendations. It incorporates three major functions: sociocultural description, preference description, and solution. In a case-based learning method, a case is described by a set of attributes or aims that identify the instance of related color recommendation for a user. Sociocultural and preference descriptions are documented using natural language descriptors or a linguistic scale.

If the proposed recommendation system has been successfully applied to a case, it will be considered as a successful case. All the successful cases are retained in an SCD as case-based learning rules. These successful cases provide a knowledge support for the proposed color recommendation system. A new user of this system will be registered as a new case. The data of the new case will be matched with the existing cases of the SCD using the similarity degree measurement.

A case is a two-tuple, i.e.  $C_j = \langle \langle f_i: v_{ij} \rangle \mid i = 1, \dots, n, f_i \in F, v_{ij} \in V_i \rangle, \langle CR_j \rangle, \langle V_i \rangle, \langle CR_j \rangle$ , where  $n$  is the number of all the user's descriptive features,  $f_i$  is the  $i$ th descriptive feature,  $F$  is the set of all features,  $v_{ij}$  is the current value of  $f_i$  in Case  $C_j$ , and  $V_i$  is the set of all values corresponding to  $f_i$ , and  $CR_j$  is the user's satisfied CR in the case  $C_j$ . For example, a specific case  $C_1$  can be expressed by  $C_1 = \langle \langle \text{Nationality: French} \rangle, \langle \text{Education background: Medical master} \rangle, \langle \text{Religion: Catholic} \rangle, \langle \text{Age: 34} \rangle, \langle \text{Gender: male} \rangle, \langle \text{Color temperature perception: very cold} \rangle, \langle \text{Color distance perception: a little closed} \rangle, \langle \text{Successful recommendation frequency: 1} \rangle, \{ \text{Color 1: P26, Color 2: P23, Color 33: P44} \} \rangle$ . In this example, we have 8 user's descriptive features ( $n = 8$ ).

$F$  includes three types of features: users' sociocultural attributes, color image perception attributes, and successful recom-



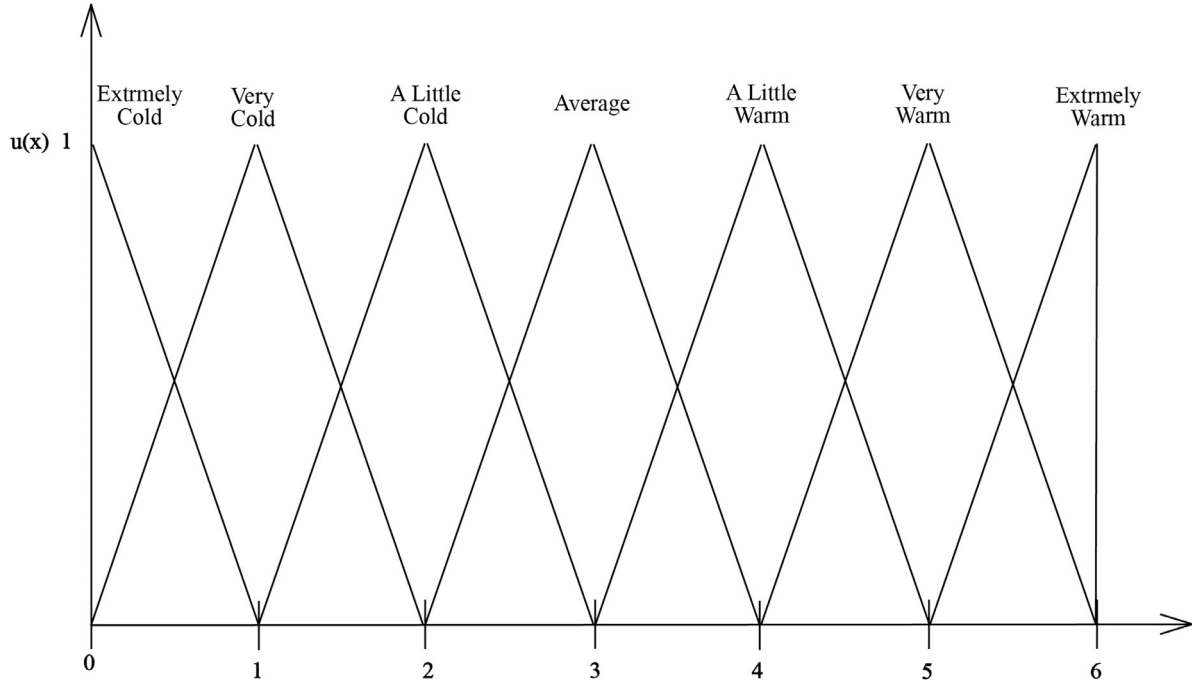


Fig. 5. Fuzzy linguistic rating scale of "cold-warm" degree.

mentation frequency. Related to personalized color preference, the sociocultural attributes include gender, education, religion, nationality, etc. These sociocultural attributes have been chosen from a wide range used in the related literature. For a specific application, the feature selection process has been conducted through interactions with a number of experts. Natural linguistic descriptors are used to describe the sociocultural attributes. Color image perception attributes are defined using the predefined BCSAs. The successful recommendation frequency describes the frequency of the concerned case, which will be recommended to a new user and can be accepted by him/her directly.

### 2.2.5. Data acquisition, quantification, and processing

The data in the proposed system is acquired from the evaluations of both designers and consumers. This data is presented as linguistic descriptors or terms that contain uncertainty and imprecision [13]. In this situation, fuzzy sets are used for analyzing and modeling the data [15]. Using fuzzy sets, all of the concerned linguistic data can be quantified for further data processing [16]. For example, when measuring a user's color image perception on the BSCA "Cold - Warm", his/her preference is initially defined using a fuzzy linguistic rating scale of {*extremely cold*, *very cold*, *rather cold*, *average*, *rather warm*, *very warm*, *extremely warm*}, as presented in Fig. 5.

Using this scale, different linguistic terms can be assigned to describe the evaluation results of the color image perceptual data. Based on fuzzy set theory, these linguistic terms will be quantified into fuzzy numbers [19]. In this study, Triangular Fuzzy Numbers (TFNs), as classic fuzzy numbers, are used to quantify linguistic terms as presented in Table 1 [17].

A TFN,  $M$ , can be denoted as  $M = (t_1, t_2, t_3)$  [5]. The parameters  $t_1, t_2$  and  $t_3$ , represent the smallest possible value, the most possible value, and the largest possible value that describe the fuzzy event  $M$ , respectively, as presented in Fig. 6 [6].

Table 1  
Fuzzy linguistic rating scale and corresponding TFNs.

Linguistic rating terms	TFNs ( $F_b$ )
Extremely warm	(5,6,6)
Very warm	(4,5,6)
A little warm	(3,4,5)
Average	(2,3,4)
A little cold	(1,2,3)
Very cold	(0,1,2)
Extremely cold	(0,0,1)

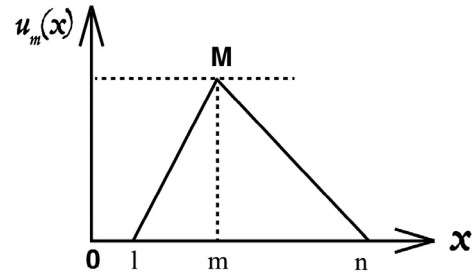


Fig. 6. The Triangular Fuzzy Number.

Each TFN has linear representations on its left and right sides such that its membership function can be defined as follows:

$$\mu_m(x) = \begin{cases} 0, & x \in [-\infty, t_1] \\ \frac{x-t_1}{t_2-t_1}, & x \in [t_1, t_2] \\ \frac{t_2-t_3}{x-t_3}, & x \in [t_2, t_3] \\ 0, & 0, x \in [t_3, +] \end{cases} \quad (1)$$

If  $M_1 = (l_1, m_1, u_1)$  and  $M_2 = (l_2, m_2, u_2)$  are two TFNs, the operation laws between them can be defined as follows [6]:

$$M_1 \oplus M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (2)$$

$$M_1 \odot M_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (3)$$

$$\lambda \odot M_1 = (\lambda l_1, \lambda m_1 \lambda u_1), \lambda \in R \quad (4)$$

$$(l_1, m_1, u_1)^{-1} = \left( \frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1} \right). \quad (5)$$

where  $\oplus$  denotes extended summation of two TFNs, and  $\odot$  denotes extended multiplication.

### 2.2.6. Representation of knowledge and related knowledge bases (DCDKB and SCD)

A knowledge base is a technology used to store complex structured and unstructured information used by a computer system. It represents facts about the world and an inference engine that can reason about those facts and use rules and other forms of logic to deduce new facts or highlight inconsistencies [29]. In this context, we created two knowledge bases for color recommendation. They include the Successful Case Database (knowledge container for all successfully recommended cases), and DCDKB (knowledge container for designers' general color design knowledge) (Fig. 3).

DCDKB contains the designer's knowledge, which is represented by their color perceptions of the CIWs, namely the measured relations of the Color Image Words (CIWs) regarding Basic Color Sensory Attributes (BCSAs). In this study, this knowledge is extracted by a series of Kansei-based human evaluations by a group of professional designers. The color image of 180 CIWs is then identified in a novel CIS regarding BCSAs by these designers. Using fuzzy set theory, the group of designers' evaluation data about their color image perception can be quantified and then aggregated. The aggregation procedure of perceptual data, provided by of [23] will enable to merge the designers' evaluation for generating a normalized and unique color image of each CIW in the CIS by all the involved designers.

Let  $X$  be the evaluation vector of the relations between one specific CIWs (emotional words) and  $w$  BCSAs (non-emotional basic attributes). Let  $F_b$  be a set of seven linguistic scores  $\{F_1, F_2, F_3, F_4, F_5, F_6, F_7\}$  (as described in Table 1). In order to quantify the linguistic evaluation data, we transform them into their TFNs, denoted as  $TFN(F_b)$  ( $b=1,2,3,\dots,7$ ), which are uniformly distributed on the interval of  $[0,6]$  [1], where  $TFN(F_1)=(0,0,1)$ ,  $TFN(F_2)=(0,1,2)$ ,  $TFN(F_3)=(1,2,3)$ ,  $TFN(F_4)=(2,3,4)$ ,  $TFN(F_5)=(3,4,5)$ ,  $TFN(F_6)=(4,5,6)$ , and  $TFN(F_7)=(5,6,6)$ .

The extraction of designer's knowledge is a group decision-making process. Using fuzzy set theory, a group decision-making with multiple designers on relations between the CIWs and BCSAs can be realized. The perceptual data provided by designers on a specific CIW can be aggregated to obtain a normalized color image perception in the newly generated CIS. In order to process this data, an aggregation method is used in this study to obtain the normalized and unique color image of a CIW regarding BCSAs [23].

Let  $TFN(F_{b1})$ ,  $TFN(F_{b2})$ , and  $TFN(F_{b3})$  represent the smallest possible value, the most possible value, and the largest possible value of  $TFN(F_b)$  respectively. Let  $N(F_b)$  ( $b=1,2,3,\dots,7$ ) be the number of evaluators selecting the score  $F_b$  (Table 1) during the evaluation experiment, the aggregated value of  $a_m$  can be defined as:

$$a_m = \left( \frac{\sum_{b=1}^7 TFN(F_{b1}) \times N(F_b)}{\sum_{b=1}^7 N(F_b)}, \frac{\sum_{b=1}^7 TFN(F_{b2}) \times N(F_b)}{\sum_{b=1}^7 N(F_b)}, \frac{\sum_{b=1}^7 TFN(F_{b3}) \times N(F_b)}{\sum_{b=1}^7 N(F_b)} \right) \quad (6)$$

For example, for exploring the relation between the CIW  $k_{1=Romantic}$  and one BCSA  $a_{1=Cold/Warm}$  (Temperature), we have mobilized 31 experts for the evaluation. If one expert considers that  $k_{1=Romantic}$  is "A little cold", three experts determine that  $k_{1=Romantic}$  is "Average between cold and warm", eight experts

think that  $k_{1=Romantic}$  is "A little warm", nine experts believe that  $k_{1=Romantic}$  is "Very Warm", and ten experts conclude that  $k_{1=Romantic}$  is "Extremely Warm", based on Eq. (6), the relation of the CIW ( $k_{1=Romantic}$ ) and the BCSA ( $a_{1=Cold/Warm}$  (Temperature)) can be expressed as follows:

$$\begin{aligned} & (0 * TFN(F_1) + 0 * TFN(F_2) + 1 * TFN(F_3) + 3 * TFN(F_4) \\ & + 7 * TFN(F_5) + 9 * TFN(F_6) + 10 * TFN(F_7)) / 31 \\ & = (3.677, 4.645, 5.29) \end{aligned}$$

It means that the aggregated result is also a TFN fuzzy number, whose most possible value is 4.645 (between  $F_5$  and  $F_6$ ), with 3.677 and 5.29 as the smallest possible and largest possible values respectively. Similarly, the associations between the CIW  $k_{1=Romantic}$  and other BCSAs can also be quantified. A vector of color image perception for the CIW  $k_{1=Romantic}$  can be obtained. The dimension of this vector is decided by the number of the BCSAs.

SCD, including all successfully recommended specific cases, is a case-based knowledge base. These cases are progressively integrated into the system for further recommendations through computation of similarity degrees between features of new and former cases. In this context, the knowledge base can become more and more complete.

### 2.2.7. Similarity measurement

The proposed recommendation starts with case retrieval, which is also the most important process in the case-based learning recommendation system. When a new user  $C$  is introduced to the proposed system, a case retrieval process will be performed. First, the sociocultural attributes of  $C$  are matched with the cases of the SCD in order to find those who has the same values in the category of the sociocultural attributes. The extracted cases constitute a subset of the SCD, denoted as  $SCD_{SC} = \{C_1, C_2, \dots, C_m\}$ . Next, we calculate the similarity degrees of the color image perception attributes of the user  $C$  with those of the cases in  $SCD_{SC}$  in order to find the target query case corresponding to the maximal similarity degree. As values of the color image perception attributes are TFNs, this similarity degree is calculated from the corresponding Euclidean distance, i.e. Similarity  $(C, C_i) = 1 - \text{Distance} - C, C_i$  for  $i=1, \dots, m$ .

If there are two TFNs  $\tilde{n} = (n_1, n_2, n_3)$  and  $\tilde{m} = (m_1, m_2, m_3)$ , the distance between  $\tilde{n}$  and  $\tilde{m}$  is denoted as the following:

$$d(\tilde{n}, \tilde{m}) = \sqrt{\frac{1}{3} [(n_1 - m_1)^2 + (n_2 - m_2)^2 + (n_3 - m_3)^2]} \quad (7)$$

For making significant comparisons, we formalize the distance or dissimilarity between  $\tilde{n}$  and  $\tilde{m}$  so that it is uniformly distributed in the interval  $[0, 1]$ , i.e.

$$d(\tilde{n}, \tilde{m}) = \frac{\sqrt{\frac{1}{3} [(n_1 - m_1)^2 + (n_2 - m_2)^2 + (n_3 - m_3)^2]}}{10}. \quad (8)$$

Therefore, the similarity between  $\tilde{n}$  and  $\tilde{m}$  could be described as following:

$$\begin{aligned} s(\tilde{n}, \tilde{m}) &= 1 - d(\tilde{n}, \tilde{m}) \\ &= 1 - \frac{\sqrt{\frac{1}{3} [(n_1 - m_1)^2 + (n_2 - m_2)^2 + (n_3 - m_3)^2]}}{10}. \end{aligned} \quad (9)$$

In our study, this similarity degree is applied in two aspects: (1) comparing the user's color image perception with that of CIWs predefined by designers in the database regarding all the BCSAs, and (2) searching for the most relevant case (target case) from an SCD predefined in the system when introducing a new user.

**Table 2**  
Definition of Basic Color Sensory Attributes (BCSAs) involved in the proposed Color Image Space (CIS).

Color sensory category	BSCAs	Color sensory category	BSCAs
Temperature	Cold–Warm	Excitement	Calm–Exciting
Distance	Forward–Backward	Freshness	Gloomy–Chipper
Weight	Light–Heavy	Construction	Plain–Abundant
Volume	Closed–Open	Hardness	Soft–Hard
Brightness	Dark–Bright	Gender	Masculine–Feminine

### 3. Experiments

To realize the proposed system, three experiments are performed. The first one is designed to establish the proposed CIS and determine the related BSCAs. The second is intended to define the sociocultural attributes that are associated with a specific user's color image perception. In the third experiment, a number of designers are invited to evaluate the 180 CIWs in the proposed system adapted from the Color Image Scale developed by Kobayashi [21]. The color design knowledge is extracted in the second experiment.

#### 3.1. Experiment I: establishment of the proposed CIS and determination of the related BSCAs

In *Experiment I*, a set of BSCAs concerning color image perception is carefully defined. These BSCAs constitute the unique CIS that can be used to measure color-image perceptions for both designers and consumers.

For this purpose, we perform a knowledge-based Kansei evaluation process procedure. The selection of BSCAs is carried out according to the following two principles: (1) the selected BSCAs should be easily understood by both designers and consumers with respect to the image of color, (2) BSCAs with ambiguity and uncertainty should be removed. Based on the stated selection principles, *Experiment I* is described as follows. It is a procedure of descriptive and quantitative Kansei evaluation. Thirty experienced designers are invited to participate in the BSCA selection. A training section is organized in order to help these designers to understand the purpose of this experiment. Each trained panellist generates an exhaustive list of color sensory categories and their descriptive BSCAs describing color image perceptions according to his/her professional knowledge. Then, a screening procedure is performed by a “round table” discussion among all of the invited designers to select the most appropriate BSCA criteria and corresponding BSCAs. This step leads to the generation of normalized descriptors describing the basic feeling of the color image. Finally, we obtain 10 normalized color sensory categories and their descriptive BSCAs, which are considered normalized basic criteria for the proposed CIS as presented in Table 2. Thereafter, each BSCA is expressed with a fuzzy linguistic rating scale of seven scores (See Table 1). Additionally, the corresponding Numerical equivalence value of each linguistic score is also given in Table 1.

#### 3.2. Experiment II: selection of sociocultural attributes related to the user's personal profile

Experiment II is designed to select the most appropriate sociocultural attributes of the user's personal profile. The process of selection follows the procedure in Experiment I. Finally, 4 attributes are selected. These attributes are represented by the choice of data type in the database, as presented in Table 3.

**Table 3**  
Different Sociocultural attributes involved in the user's personal profile.

Sociocultural attributes	Description	Data type
Gender	F/M	Choice
Nationality	A list of country names	Choice
Religion	A list of religion types	Choice
Education Degree	A list of education levels	Choice

#### 3.3. Experiment III: knowledge acquisition and color image perception definition of related CIWs in CIS

In product design and development, the descriptive Kansei evaluation is usually performed by a trained panel composed of experienced experts for judging products on a number of analytical and neutral linguistic descriptors. A descriptive Kansei evaluation permits the extraction of neutral and normalized sensory descriptors and normalized sensory data describing a collection of products [38]. Independent of involved evaluators and social contexts, the evaluation is only related to the basic nature of the products and is thus considered an objectified evaluation characterizing human perceptions. Product designers can master the association of these sensory attributes with the CIWs from their professional experience.

In this section, the designer's color image perceptions of CIWs are characterized using classical descriptive Kansei evaluations. Professional knowledge is extracted and exploited in order to characterize the CIWs in the defined CIS [33]. In *Experiment III*, 30 designers are selected and invited to perform the color-image perception identification process for the related CIWs in the proposed CIS. Each of the designers is invited to give a linguistic score using the terms of Table 1 for each CIW regarding each BSCA. The corresponding formalization is given below.

Let  $K$  be a collection of  $m$  CIWs defined by Kobayashi, denoted as  $K = \{k_1 \dots k_m\}$  (initially  $m = 180$  in our case).

Let  $E$  be a set of  $l$  selected experts performing the sensory experiment, denoted as  $E = \{e_1 \dots e_l\}$  ( $l = 30$  in our case).

Let  $A$  be a set of  $p$  BSCAs describing CIWs (Table 2), denoted as  $A = \{a_1, \dots, a_p\}$ , ( $p = 10$  in our case).

Let  $D$  be a set of  $s$  normalized linguistic terms generated by a group of  $m$  trained designers for describing the human perceptions (designers and consumers) on the color image themes, denoted as  $D = \{d_1, \dots, d_s\}$ , ( $s = 7$  in our case).

Based on the previous formalization, by using the Numerical equivalence values defined in Table 1, all of the linguistic scores expressed by linguistic terms can be quantified. Then, according to Eq. (1), the evaluation data of all of the invited designers can be aggregated as a 10-dimensional vector. Using the same method as the example in Section 2.2.4, the associations of the other CIWs with the BSCAs can also be expressed. We consider that the disconformity between these trained experts is very small because they have similar professional training background on the evaluated CIWs [11]. Through this process, designers' knowledge about all the associations between CIWs and BSCAs can be extracted. The identified associations between CIWs and BSCAs can be considered as design rules or design knowledge to be used in the future recommendations.

### 4. Case study of system implementation

To verify the usefulness of the proposed color recommendation system, 81 people in France are invited to use the proposed system. Selected users have no professional knowledge about color, art or design. They are, for example, Muslims, Catholics, and Buddhists. They have different education levels, including engineering

**Table 4**Color image preference of the first user  $c_1$ 

Color sensory category	Linguistic color image perception	Color image perception in TFNs	Association of CIW $k_{1=Romantic}$ and all BCSAs
Temperature	Average temperature	(2,2.5,3)	0,914
Distance	Very forward distance	(1,1.5,2)	0,632
Weight	Average weight	(2,2.5,3)	0,982
Volume	A little closed volume	(1.5,2,2.5)	0,786
Brightness	Average brightness	(2,2.5,3)	0,893
Excitement	A little calm	(2.5,3,3.5)	0,915
Freshness	Very chipper	(3,3.5,4)	0,726
Construction	Average construction	(2,2.5,3)	0,806
Hardness	Very soft	(1,1.5,2)	0,879
Gender	A little masculine	(1.5,2,2.5)	0,925

degrees, MA degrees, and BA degrees. Their ages are distributed randomly. Also, they include 37 males and 44 females.

Each of the invited users is required to evaluate their color image perceptions on the BCSA  $d_s$  of the defined CIS. The color image perceptions of these users are recorded in the database [24]. Let  $C$  be a collection of  $n$  users, i.e.  $C = \{c_1, \dots, c_n\}$ . In our specific scenario, we have  $n = 81$ .

In order to validate the effectiveness of the proposed recommendation system, three different cases for different users are discussed.

#### 4.1. Case study I: an example of a knowledge-based recommendation process (case study of the first user)

In this case, the proposed system enables to understand the unsatisfied attributes of the current recommendation result and then recommend a new color range using the feedback procedure described previously.

The first user  $c_1$  is female. At the beginning of the recommendation,  $c_1$  is asked to input her color image preference into the system by using the linguistic scores in Table 1 for all the BCSAs in Table 2. These linguistic evaluation scores are quantified using the Numerical equivalence values in Table 1. The related data are presented in Table 4.

As the first user of this system, there is no learning rule in the SCD. Thus, only the professional knowledge is available for the recommendation. The similarity degrees between the user's color image perceptual data and that of CIWs predefined in the system are computed. The computation is performed regarding each of the BCSAs. For example, as explained in Section 3.3, the associations of CIW  $k_{1=Romantic}$  and all the BCSAs, recognized by experts is (2.8,3.383,3.883) (Table 4). Also, the color image perception of  $c_1$  related to all the BCSA is (2,2.5,3) (Table 4). Then, we calculate the similarity degree of the color image perception between  $c_1$  and  $k_{1=Romantic}$  as

$$1 - \frac{\sqrt{\frac{1}{3}[(2.8 - 2)^2 + (3.383 - 2.5)^2 + (3.883 - 3)^2]}}{10} = 0.914$$

meaning that this similarity is very high.

Similarly, the color image perception of  $c_1$  is compared with all CIWs. Thereafter, the CIW which has the highest similarity degree (95.7%), i.e.  $k_9 = Casual$ , is selected. Then, using the principle of Kobayashi (Figs. 1 and 2), the CR described by  $k_9 = Casual$  is recommended (See Fig. 7-a). It is a range of three colors: P130 (dark red), P143 (white) and P106 (dark blue).

Next, the evaluation of the recommended CR is performed by  $c_1$  in terms of the basic color physical properties (*hue, lightness, and purity*). The evaluation results of  $c_1$  include: (1) the color hue of the first recommended color (P130) should be slightly enhanced; (2) the brightness of the third recommended color (P106) should also be slightly increased. In this situation, by visualizing

the neighboring colors on the same columns (PB series and RP series) around P130 and P106 in Fig. 2, the user manually selects P132 to replace P130 and P112 to replace P106. By performing the same evaluation procedure on this new CR, we can find that it fully satisfies by  $c_1$ . The final result is presented in Fig. 7-b.

The personal profile data and color image perceptual data of  $c_1$  along with the satisfactory CR in Fig. 7-b will then be retained as the first learning rule and stored in the proposed SCD. Similarly, the recommendation processes of the other 80 users are also performed and stored as learning rules in the proposed SCD.

#### 4.2. Case study II: an example of the case-based learning process using human-machine interaction (for the 77th user)

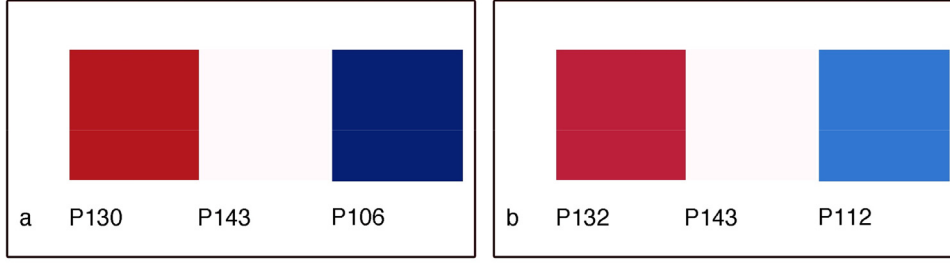
The recommendation process of the 77th user  $c_{77}$  is presented to explain the case-based recommendation process, in which the learning rules from the proposed SCD are effectively an efficient support and a new learning rule is generated from this case.

$c_{77}$  is a male user. Like Case study I, the recommendation process of  $c_{77}$  starts by inputting his personal profile and color image perception using the predefined descriptive features. First, the retrieval process is performed to check whether the historic learning data exist or not in the system by using the similarity degree. Finally, the case of the target user  $c_{32}$  in the SCD is selected because its similarity degree with  $c_{77}$  is the biggest (98.35%) and higher than the threshold (85%). Then, the recommended CR associated with  $c_{32}$  will be proposed to  $c_{77}$ . Next, an evaluation procedure is used to check for the satisfaction of  $c_{77}$ . As  $c_{77}$  is not satisfied with the recommended CR in the aspect of lightness, we start a feedback process for modifying or adjusting the recommendation result. After several interactions with the system, a final satisfied result is obtained. Then, the recommendation case of  $c_{77}$  is retained in the SCD as a new learning rule.

In this case, it has been found that the proposed system is an open system, capable of integrating new design rules along with related CRs based on the color image perceptual data of new cases. SCD can be dynamically updated through the knowledge-based recommendation and consumer feedback integrated process.

#### 4.3. Case study III: an example of the case-based recommendation process using the concept of machine learning (case study of the 80th user)

A female consumer  $c_{80}$  is introduced to the recommendation system. First,  $c_{80}$  is invited to provide her color image perception in the 10-dimensional CIS regarding all the BCSAs. Then, the personal profile and color image perception of  $c_{80}$  are compared with all of the existing cases in the SCD. According to the computation of the similarity degrees of  $c_{80}$  related to the cases in SCD, we find that there are two similar cases ( $c_{47}$  and  $c_{66}$ ) existing in the SCD, with a similarity degree of 86.8% which is bigger than the threshold of 85%. In this situation, the successful recommendation frequencies



**Fig. 7.** Color recommendation result of the first user: (a) initial recommendation and (b) adjusted recommendation after the consumer evaluation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of  $c_{47}$  and  $c_{66}$  will be compared. From the computation, we find that the successful recommendation frequency of  $c_{47}$  is 2 and that of  $c_{66}$  is 0. Therefore, this module will recommend the retained CR of  $c_{47}$  to the consumer  $c_{80}$ . Based on the evaluation of  $c_{80}$ , she is satisfied with the recommendation result reused of  $c_{47}$ . In this situation, the recommendation process for  $c_{80}$  is finished, but the case of  $c_{80}$  will not be retained in the system as a new case-based learning rule because the similar rule already exists in SCD. Also, successful recommendation frequency of  $c_{47}$  will be changed into 3.

## 5. Evaluation of the proposed color recommendation system and data discussion

In order to evaluate accuracy, scalability, and efficiency of the proposed system, different experiments are designed and analyzed. To evaluate the performance regarding accuracy, we compare between the proposed CBCRS algorithm and the two other relevant recommendation approaches: Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) [28]. These two algorithms have been applied to color recommendation in different studies [28]. The Mean Absolute Error (MAE) [31], as a metric widely used to measure the prediction accuracy, is utilized in the comparison of the accuracy of these three algorithms. To evaluate the scalability, Speedup [3], as a well-accepted scalability metric, is adopted and applied to measure the performance regarding the scalability of the proposed CBCRS algorithm. As to efficiency, the number of recommendations until obtaining satisfying results (SRTs) is defined in this study to measure the performance of efficiency.

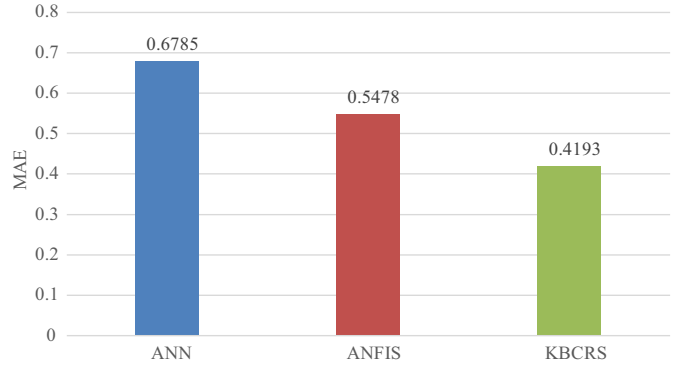
### 5.1. Accuracy evaluation

MAE is a statistical accuracy metric frequently used for measuring the prediction quality of an algorithm [31]. The lower value of MAE is, the more the prediction is accurate. In order to collect raw data for the MAE analysis, we invite 81 users to apply the three recommendation systems using ANNs, ANFIS and CBCRS respectively. Each invited user is asked to give a satisfaction degree of each system in terms of prediction accuracy.

Let  $p_t$  ( $t=1, 2, \dots, 81$ ) denote the prediction satisfaction degree of each user given for one of the system, where  $p_t \in [0,1]$ . Let  $p$  denote the ideal satisfaction degree ( $p=1$ ), MAE can be given by

$$MAE = \frac{1}{N} \sum_{t=1}^N |p_t - p| \quad (10)$$

In our experiments, the proposed MAE evaluation is based on the leave-one-out cross-validation method. According to this method, the 81 users' evaluation data are split into two sets, i.e. 80 data for training and the remaining one for testing. This procedure repeats for 81 times until each of the 81 data has been selected for



**Fig. 8.** Comparison of ANNs, ANFIS, and CBCRS using MAE.

testing. We use their averaged MAE value to represent the performance of the corresponding recommendation system. Fig. 8 shows the averaged MAE values of ANNs, ANFIS and CBCRS when recommending colors.

Fig. 8 shows the averaged MAE values of ANNs, ANFIS and CBCRS when recommending colors. It could be found that the MAE value of CBCRS (0.4193) is much lower than those of ANN (0.6785) and ANFIS (0.5478). Thus the proposed CBCRS can provide more accurate predictions than the classical methods ANN and ANFIS.

### 5.2. Scalability evaluation

Speedup is a well-accepted scalability metric, which has been used to measure the performance of an algorithm regarding the scalability [3]. Speedup is defined as follows:

$$S_p = \frac{T_1}{T_p} \quad (7a)$$

where  $p$  is the number of processors,  $T_1$  is the sequential execution time,  $T_p$  is the parallel execution time with  $p$  processors.

When the number of processors increases, if the memory capacity and network bandwidth also increase, it means this algorithm is considered scalable. For a fixed data size, the memory capacity and network bandwidth of an algorithm is represented by Speedup. If the Speedup has a linear relation with the number of processors, the algorithm is regarded as having good scalability. When the data size increase, if this kind of linear relation tends to be more obvious, this algorithm has better scalability.

To verify the scalability of CBCRS, a set of experiments were carried out. At the beginning of the Speedup evaluation, an online data collection system is firstly developed to collect raw data. Users were assigned to input all the necessary information described in Tables 2 and 3. Due to the time horizon of the system, we processed all the collected data into four synthetic datasets of different sizes (128M, 256M, 512M and 1G). For each of the synthetic datasets of different sizes, experiments were carried out us-

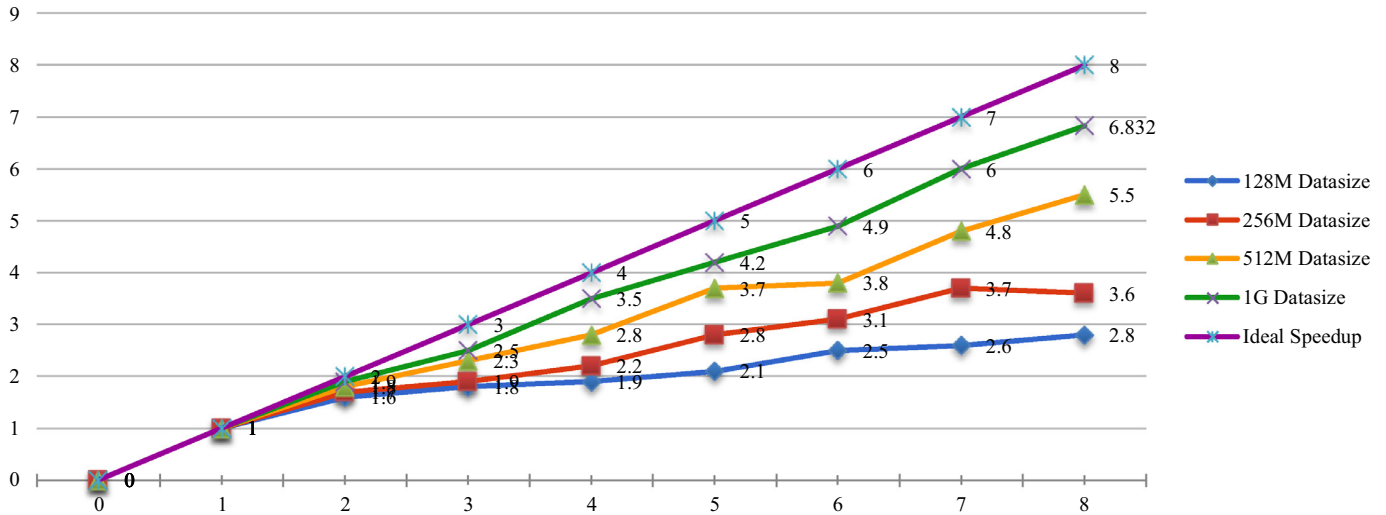


Fig. 9. Speedup of CBCRS.

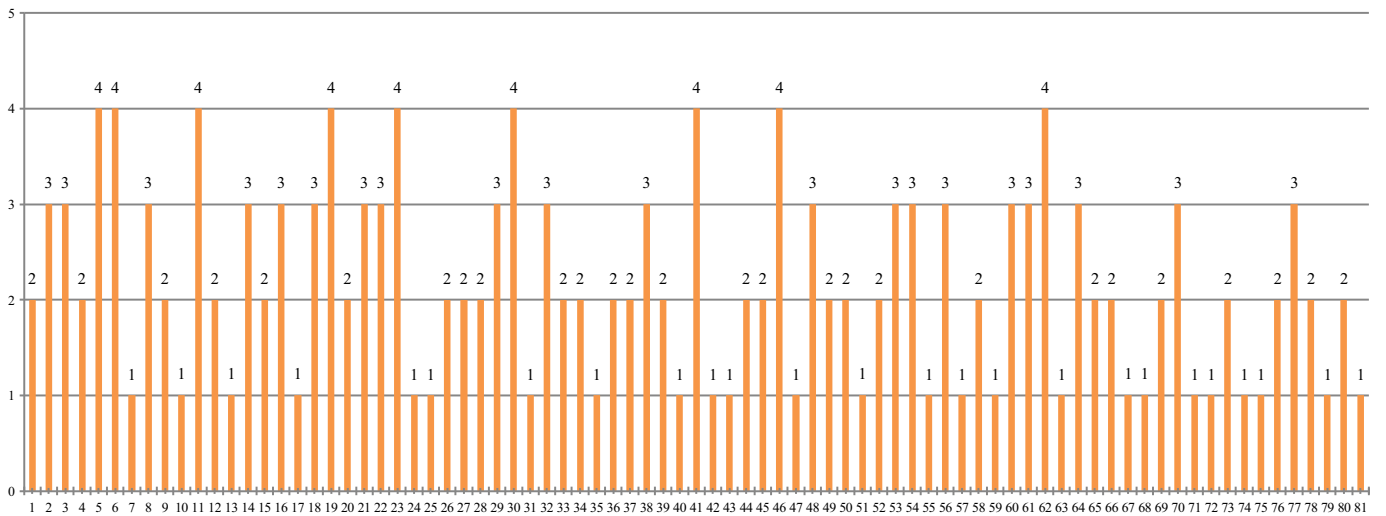


Fig. 10. Color recommendation times until obtaining satisfied results for all the users. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ing processors ranging from 1 to 8 respectively. Fig. 9 presents the speedup of the proposed CBCRS.

From Fig. 9, it can be found that, with the growth of the number of nodes, the speedup of the proposed CBCRS algorithm increases relative linearly. Meanwhile, the dataset with a larger size tends to obtain a better speedup. Specifically, when the data size is 1G and the number of nodes is 8, the speedup value reaches 6.832, which is 85.4% ( $6.832/8=85.4\%$ ) of the ideal speedup. It can be concluded that CBCRS has good scalability and performs better with larger datasets.

### 5.3. Efficiency evaluation

This section discusses the efficiency of the proposed CBCRS algorithm. For this purpose, interactions with the system of a user to obtain a satisfied recommendation result (SRTs) is defined in this study. For example, if the SRT value of a user is 1, it means that this user obtains a satisfied result through one-time interaction with the system. Lower SRT value of a case indicates that a user can obtain a satisfied recommendation result through lower interaction times with the system, which means it is more efficient.

Fig. 10 presents the SRT values of the 81 users in the experiment. We divide the 81 users into 3 groups according to their arrival time. Each group contains 27 users. For each group, the SRT frequency and the average SRT are calculated. Table 5 presents the related statistical data for each group.

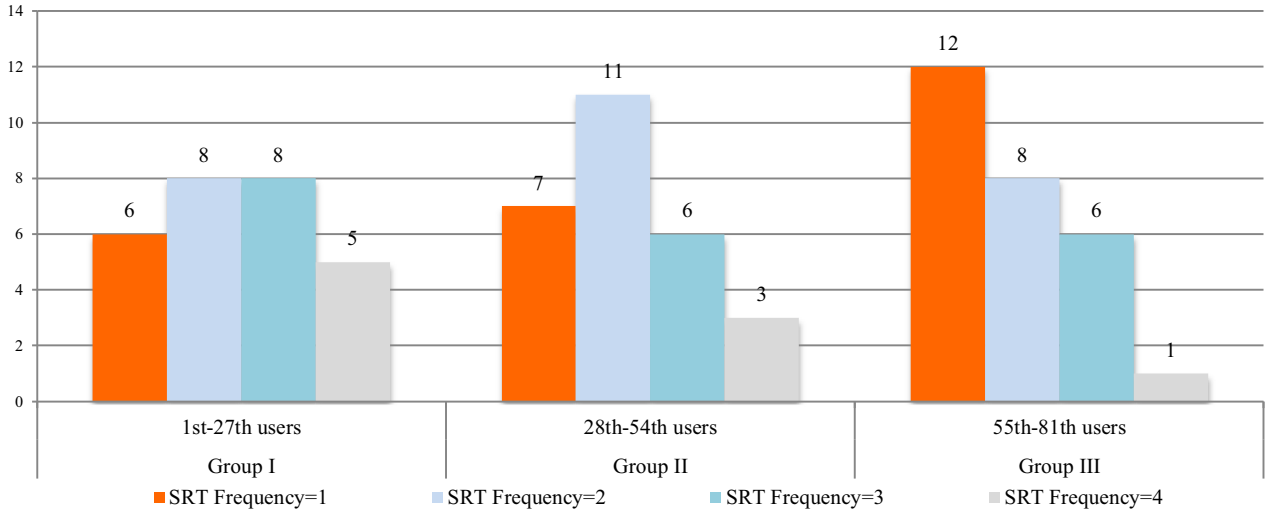
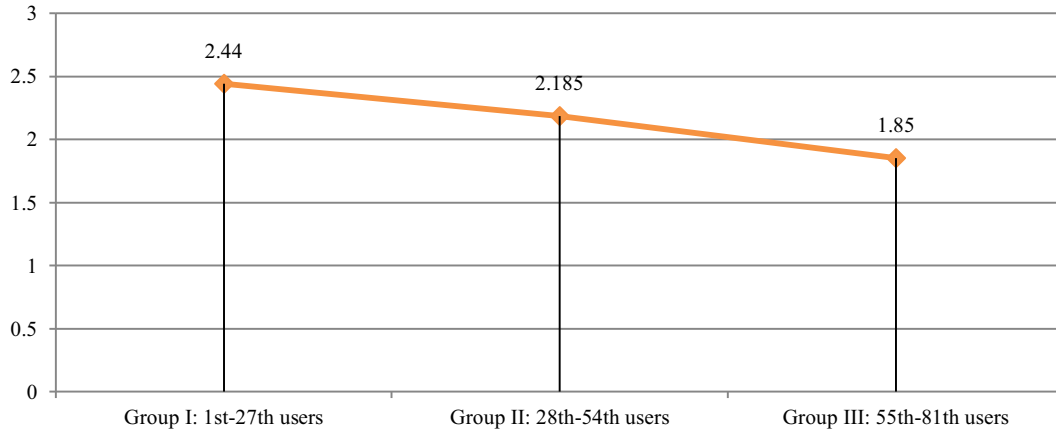
For all of the 81 cases, the highest SRT is 4, and the lowest is 1. The average SRT for all of the cases is 2.16. In 25 cases, users can obtain satisfactory recommendations after a one-time interaction with the system (30.86%). In 27 cases, the consumers can obtain satisfactory recommendations after two interactions with the system (one time of feedback) (33.33%). In 20 cases, the consumers can obtain satisfactory recommendations after three interactions with the system (two time of feedback) (24.69%). In 9 cases, the consumers can obtain satisfactory recommendations after four interactions with the system (three time of feedback) (11.11%). In total, in 64.19% of the cases, users can obtain satisfactory recommendations within two interactions with the system.

The global recommendation efficiency is rather high. Users can obtain satisfactory recommendations very quickly. Compared with the traditional color recommendation methods, the proposed knowledge-based color recommendation system, supported by case-based learning and design knowledge, can recommend

**Table 5**

SRT Frequency and average SRT for different groups.

Number of times needed for a successful recommendation		Group I 1st-27th users	Group II 28th-54th users	Group III 55th-81th users	Total
SRT Frequency	1	6 (22.2%)	7 (25.9%)	12 (44.4%)	25 (30.86%)
	2	8 (29.6%)	11 (40.7%)	8 (29.6%)	27 (33.33%)
	3	8 (29.6%)	6 (22.2%)	6 (22.2%)	20 (24.69%)
	4	5 (18.5%)	3 (11.1%)	1 (3.7%)	9 (11.11%)
Average SRT	2.44	2.185	1.85	2.16	

**Fig. 11.** Distribution of SRT frequencies for different groups.**Fig. 12.** Average SRTs for different groups divided by time order.

faster and more satisfying results. As the system is able to understand the unsatisfied attributes of the user when evaluating the recommended color range, and can dynamically modify the recommendation result, the proposed system can be more adapted to the changes of the outside environment.

Fig. 11 presents the SRT frequency of three different groups divided according to time order. In the first 27 cases, 6 users obtain satisfactory recommendations after one interaction with the system (22.2%). In the second group of 27 cases, 7 users obtain satisfactory recommendations after one interaction with the system (25.9%). In the third group of 27 cases, 12 users obtain satisfactory recommendations after one interaction with the system (44.4%). In other words, the rate of success for recommendation is increasing when the system is used by more and more users and the corresponding SCD is enhanced.

Fig. 12 presents the average SRTs for different groups divided by time order. Fig. 8 shows that the average SRT decreases when the

proposed recommendation system is applied by more and more users.

Figs. 7 and 8 show that, by using the case-based learning mechanism, users' color image perception can be easily captured and progressively understood by the proposed system. The system is able to find a similar case for recommendation to a new user when the number of cases stored in the SCD is important. When the number of users of the proposed color recommendation system is increasing, more learning rules can be generated in order to further improve the recommendation quality. In this way, the working efficiency of color recommendations can be largely increased with reduced costs.

#### 5.4. Complexity comparison

In the specific scenarios of color recommendation, the comparison of complexity between the three concerned methods (feed-

**Table 6**  
Complexity comparison: ANN, ANFIS and CBCRS.

Complexity comparison	ANN (MLP)	ANFIS	CBCRS
Number of parameters	20	28	13
Number of training iterations	3	20	3
Training time (sec)	0.504	0.008	0.002

forward ANN with back propagation algorithm, ANFIS and CBCRS) can be performed by measuring the number of parameters of each model, number of training iterations and number of updating. The number of training iterations corresponds roughly to stopping the training when the minimum of model prediction error is achieved. The comparison results are shown in Table 6.

From these results, we can find that the proposed CBCRS method is more performant than ANN and ANFIS in terms of training time, number of training iterations and number of parameters. In fact, CBCRS is based on computation of similarity degrees and the number of its parameters is much less than the other methods.

## 6. Conclusion

This paper presented a case-based color recommendation system for recommending the most appropriate CR based on the user's color image perception of the user related to a set of BC-SAs. The proposed system is based on case-based learning. A set of success cases is retained in an SCD, including user's sociocultural data (gender, religion and education background and other cross-cultural background factors), as well as color image perceptual data and satisfactory CRs. These satisfactory CRs can be obtained from the latest color trend based on open resources, supported by a knowledge-based Kansei evaluation process. The working procedure of this system uses a sequence of *Recommendation – Display – Evaluation – Adjustment* until a satisfactory result is obtained. When a new consumer uses the system, the similarity degree of his/her personal profile and color image perception will be measured related to the retained cases in the SCD. If the maximal similarity degree between the new consumer and the successful cases in SCD is higher than the predefined threshold, the stored color recommendation results of the corresponding case in SCD will be reused for the new consumer. If the new consumer is not satisfied with the result, his/her color image perception will be analyzed by the system and a new recommendation using the updated design rules will be delivered until the user is satisfied. In this situation, the successfully applied cases (user's sociocultural data, color image perceptual data, and satisfactory CRs) will be continuously integrated into the SCD in order to enhance the accuracy of recommendation.

In the proposed system, a 10D CIS is initially established by using BC-SAs to measure color-image perceptions of both designers and consumers. These BC-SAs are carefully selected, which can be easily understood by untrained people. Using the proposed CIS, the related 180 CIWs related to mood, lifestyle and taste are measured in terms of the BC-SAs by designers using a procedure of Kansei evaluation. These CIWs are measured using a set of linguistic terms, which are then quantified by fuzzy sets. Thereafter, the color images of these CIWs can be properly located in the proposed CIS using the professional knowledge of the designers. As a group decision-making method, high accuracy of CIW measures is ensured. Similarity measurement tools play very important roles in the proposed system, ensuring the understanding of the user's color image perception by retrieving the color image perception of the system user and the most similar CIWs predefined by the designers' group decision-making.

The proposed recommendation system is a dynamical self-learning system. New color ranges can be generated according to the change of the user's color image perceptual data, and also from the color trend based on open resources. Compared with other prediction methods, such as linear regression, the proposed method is more robust and interpretable due to its capacity for treating uncertainty. Additionally, recommendations of the proposed system are based on the similarity measurements between cases, which means common sociocultural limits in the color recommendation, such as differences in language, nationality and culture, can be avoided. Additionally, the proposed novel BC-SAs can be further applied to the perception analysis of customers for color-related products. The result of this work could also be extended to support the area of personalized industrial product design such as fashion design, furniture design and advertisement design. Through a series of real applications, the proposed color recommendation system supported by case-based learning has demonstrated the implication of case-based decision-making in a scaleable data environment.

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