Interactive genetic color matching design of cultural and creative products considering color image and visual aesthetics

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ABSTRACT

To optimize the colors used in cultural and creative products, this paper proposes a color matching design method that considers the color image and visual aesthetics. First, 99 color samples are identified based on Chinese traditional colors, and user preferences for 30 image semantic terms are measured by the semantic differential method. This leads to six color image factors being extracted by factor analysis. Second, quantitative analysis of the color visual aesthetics is applied, and formulas for calculating the harmony, balance, and symmetry are derived. On this basis, an interactive genetic algorithm is developed to promote and optimize the color scheme of cultural and creative products, and a fitness function based on subjective image evaluation and objective visual aesthetics is constructed. The subjective image evaluation adopts interval numbers, and a grayscale approach is used to measure the uncertainty of the subjective evaluation. Through grayscale analysis of the interval fitness values, information reflecting the evolutionary distribution of the population is extracted, before adaptive crossover and mutation probabilities are applied to the evolutionary individuals. Finally, the proposed method is verified through the example of color matching design for a speaker box. The results demonstrate that the proposed approach can effectively assist industrial designers.

1. Introduction

In recent years, the Chinese government has actively introduced various policies to promote the development of cultural and creative industry. The revenue of cultural and creative products of Beijing Forbidden City reached 1.5 billion yuan in 2017. The Forbidden City is just a microcosm of the development of China's cultural and creative industry, and the future of cultural and creative industry will be promising. Cultural and creative industry is an emerging industry with creativity as its core, which arises in the context of economic globalization. Cultural and creative products refer to any product or combination of products produced in the cultural and creative industry.

In terms of the final form of products, cultural and creative products contain two interdependent parts: cultural and creative contents and carriers. The spiritual and emotional value of cultural and creative contents endows the experience value and economic value to cultural and creative products. Based on conventional products, cultural and creative products attempt to integrate the cultural characteristics of a country, nation, or region. Such products have both cultural and innovative attributes, combining traditional culture with innovative design.

Color matching is an important constituent part of product design, playing a significant role in product style and image positioning. In the color design of cultural and creative products, the characteristics and attributes of the target culture are used to determine the colors reflecting the target region, and these are applied to specific products in combination with the designer's creativity. Compared with conventional product color design, this approach utilizes more of the typical regional, cultural, and contemporary features (He et al., 2020). The commercial age has accelerated product development. It is now difficult for designers to fully understand all the meanings of culture when designing a culturally representative product color scheme in a short period of time.

With the development of the experience economy, product color design must pay attention to consumers' aesthetic and emotional experiences. Traditionally, color matching design is completed by the designer according to the design experience, and there is room for improvement in both the accuracy and intelligence of the design. At present, various intelligent optimization algorithms, such as neural networks, artificial bee colony algorithms, and genetic algorithms, can be used to find color schemes that conform to certain aesthetics and images, helping designers to improve their design efficiency and success rate.

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Current cultural and creative product design focuses on image-inspired color schemes, transposing color matching schemes from traditional culture into modern products. However, color image can be affected by the carrier type, function, form, and use environment. Applying the same color scheme to different products in different environments will produce different image effects. This poses a challenge to intelligent color matching technology. It is better to complete color matching through human–computer cooperation, which allows people to deal with the parts that are difficult to be completed by the algorithm.

Thus, based on interactive genetic algorithms (IGAs) with a grayscale of interval fitness (Guo and Cui, 2008), we propose a color matching design method that considers the color image and visual aesthetics. Through user evaluation of evolutionary individual fitness, the problem of imagery differences of the same color scheme applied to different 3D products is solved. We have three main contributions. First, the traditional Chinese colors are used to build color samples and to construct a semantic mapping space of color samples and color image, which is suitable for oriental aesthetics. Second, in the process of interactive genetic evolution, the fitness value consists of two components: a subjective image evaluation value and an objective visual aesthetics value. The weights of the two can be adjusted according to the desires of the decision-makers (for example, whether they have a background in design). Third, we propose to quantitatively analyze the visual aesthetics of color matching of cultural and creative products in terms of harmony, balance, and symmetry. Meanwhile, the subjective evaluation value is expressed as an interval, and the grayscale is used to evaluate the uncertainty of user evaluations.

We surveyed and discussed allied work by drawing on previous studies regarding product color design, color theme extraction, and intelligent design system (Section 2). The design process of color matching is proposed, as shown in Figure 1. First, a color sample library is established based on traditional Chinese colors (Section 3). Second, a semantic differential experiment is implemented to ascertain the user’s color image (Section 4.1). Third, the visual aesthetics of color matching of cultural and creative products are quantified from three aspects: harmony, balance, and symmetry (Section 4.2). Fourth, interactive genetic evolution is used to obtain a color scheme that conforms to the emotional perception and aesthetic principles of the target image (Section 5). Fifth, a color matching design case of a speaker box is used to verify the performance of the proposed method (Section 6). Finally, a discussion and conclusion are presented (Sections 7 and 8).

2. Related works

Previous work related to this paper consists of three main aspects: product color design, color theme extraction, and intelligent design system.

2.1. Product color design

At present, with the development of Kansei engineering (Nagamachi, 2002) and computer technology, the research on product color design focuses on the following three aspects (Zhao et al., 2018):

(1) The color harmony theory is used to satisfy the aesthetic and emotional preferences of users. For example, Hsiao et al. (2017) proposed a method of evaluating aesthetic measures of product images using color matching, and aesthetic measure theory has been used to quantify the aesthetics of color harmony. Guo et al. (2020) optimized the color of tricolor products considering color harmony and users’ emotional preferences simultaneously.

(2) Kansei engineering theory can be used to capture consumers’ psychological feelings on colors and design product color images. For example, Ding et al. (2013) constructed a color design model for products with multiple emotions, factor analysis, Procrustes analysis, and particle swarm optimization to find the color scheme and satisfy the complex and multidimensional emotional expectations of consumers. Li et al. (2017) took the multi-user color image as a decision factor and proposed a color decision system based on an improved particle swarm optimization algorithm to optimize an artificial neural network.

(3) Intelligent algorithms can be used to automate product color design. For instance, Sun et al. (2007) performed product color matching based on a genetic neural network. Liu et al. (2009) studied the automatic mapping mechanism of a color scheme from a plane image to a 3D product model, and used an interactive genetic algorithm to determine the optimal scheme. Under the constraint of the color harmony evaluation mechanism, Liu et al. (2012) selected and optimized color combinations using an interactive genetic algorithm, with color semantic contribution factors and user interactive assessment results applied as evolution conditions. Zhao et al. (2018) applied a multi-objective hybrid artificial bee colony optimization algorithm to the problem of the relative fuzziness of color matching results. To embody users’ preferences into product color design, Yang and Tian (2019) used an improved interactive genetic algorithm to reduce user cognitive noise and promote convergence.

Intelligent design is one of the research trends of color matching design, and there is a lot of work to be done to quantify the color matching principles and people’s preferences.

2.2. Color theme extraction

Color theme extraction is quite important in several fields, such as automatic color design, image categorization, clothing matching on color, and interior design. Color theme can be extracted from an image manually by humans or automatically by a software. The plenty of automatic color theme extraction methods, either supervised or unsupervised, have been presented (Ciocca et al., 2019). By using visual saliency, Jahanian et al. (2015) extracted the fine colors appearing in the foreground along with the various colors in the background regions of an image. Wang et al. (2016) proposed an artistic balanced color theme extraction algorithm aimed specially at paintings. Liu et al. (2018) designed a color selection strategy to extract the colors with high saliency, color diversity, and low coverage error. They reported a method that can efficiently transfer colors between two fabric images for fabric color design. Liu and Luo (2016) combined color emotion theory with color theme extraction, and presented a novel hierarchical emotional color theme extraction method. Su and Sun (2019) developed a novel framework for the color transfer between color images, which can further achieve emotion transfer between color images based on the human emotion (human feeling) or a predefined color-emotion model. Weinerl et al. (2020) presented a framework for building a model for extracting prominent colors from the image based on machine learning.

The color design of cultural and creative products requires the analysis of typical colors in traditional culture. Scholars have studied the color matching laws of traditional clothing colors (Zhao, 2014), ancient opera colors (Yang, 2013), traditional mural colors (Zhang, 2009), and other objects of traditional Chinese culture. In terms of color extraction
methods (Xu et al., 2019), research has mainly focused on obtaining a large number of color configuration schemes from 2D cultural images and building a color configuration scheme library for 3D product color matching design. For example, Liu et al. (2016) developed an assistant technology for color matching design based on a color network, extracted a range of characteristic colors from the traditional pattern library using K-means clustering, and recommended the color matching scheme that best reflected the original cultural appearance for designers. Hsiao et al. (2015) used an artificial neural network system to simplify the collected five categories of pictures representing Taiwanese culture. Wang (2018) applied fuzzy C-means clustering in the design of cultural and creative products. Y. Zhu et al. (2020) extracted feature colors from the Dunhuang mural gallery and mapped the extracted color combinations to plane patterns for color matching design. Chen et al. (2015) proposed a perceptual design method for product color matching based on the reuse of a color configuration scheme, obtained the color combination scheme from the source image using technologies such as fuzzy processing and main color extraction, and established a color configuration scheme library that reflects the cultural characteristics of wooden houses of Miao and Dong nationality. It can be seen that the principles and technology of color extraction are very mature, and a color extraction plug-in based on the CorelDRAW platform has even been developed (Liu et al., 2016), allowing the colors of the source image to be quickly extracted.

There are abundant color extraction techniques available. For the color matching design of cultural and creative products, scholars mainly extract color from two-dimensional cultural images. Whether the color transfer applied to the 3D product meets the emotional needs of users needs to be further studied.

2.3. Intelligent design system

IGAs are part of the evolutionary algorithm family (Gong et al., 2007). Their main feature is to evaluate the fitness of individuals in the population through human interaction. IGAs are often used in difficult structured tasks such as art, design, composition, creation, and so on (Hsiao et al., 2013). For example, Dou et al. (2016) proposed a multi-stage interactive genetic algorithm and applied it to the car console conceptual design system, to capture the knowledge of users’ personalized requirements. Dou et al. (2019) proposed a combined Kano model and IGA approach and developed a computer-aided design system prototype in the context of the customized design. Wang and Zhou (2020) proposed a method of interactive genetic algorithm with the interval arithmetic based on hesitation and fuzzy kano model to explore the emotional needs of users, and created a product evolution design system platform, which can automatically generate product styling design scheme in line with user preferences.

IGAs are suitable for human–computer collaboration in color matching design tasks. For instance, Hsiao et al. (2013) proposed a consultation and simulation system for product color planning that helps designers obtain the optimal color planning for components and decorative patterns of a product. By utilizing the VBA macro editor of CorelDRAW software, Yang and Tian (2019) developed an interactive product color design module by combining users’ cognition noise and an IGA. Wang et al. (2021) established multiple constraints based on various color requirements from the product color matching design, and calculated the final color planning scheme by the Matlab software.

Therefore, IGAs can be used in color matching design. However, the application of IGAs to color matching design has some shortcomings. If only the subjective evaluation of people is used as the evolutionary standard, there will be individual differences caused by individual cultural backgrounds and preferences. Additionally, people are prone to fatigue, and the uncertainty of user assessment leads to the problem of evaluation noise (Zhang and Yang, 2019). Therefore, in the interactive evaluation process, we propose to use interval numbers to evaluate the color scheme, and the grayscale is used to measure the uncertainty of the evaluation. The adaptive crossover and mutation probabilities of evolutionary individuals are given by the grayscale analysis of the interval fitness value, thus relieving user fatigue (Guo and He, 2009).

3. Color samples based on traditional Chinese colors

Colors come from nature. From observing the natural scenery between the movement of heaven and earth, sunrise and sunset, and the change of time sequences, our Chinese ancestors learnt the concept that red, green, yellow, white, and black are the five basic colors of the universe and earth, giving rise to the theory of the “five color view.” Chinese culture has been handed down for thousands of years. The color names are full of moral and poetic meaning. In 2008, the five Olympic mascots took the blue of traditional blue and white porcelain, the grey of the Great Wall of China, the yellow of colored glaze, and the green of the Chinese scholar tree as the source for their color design, carrying the essence of Chinese culture. Guo and Li (2020) rigorously researched 384 traditional Chinese color names by examining the color-related literature. According to the 24 solar terms and 72 phenology types, 96 pieces in the Palace Museum were selected to extract the traditional colors from hundreds of thousands of cultural relics. Taking time as the axis and relying on cultural relics demonstrates the traditional Chinese color system.

The principle of selecting color samples reduces the number of samples as much as possible while satisfying the premise of color image expression, thus reducing the evaluation burden of subjects. To eliminate visually indistinguishable colors, 96 traditional colors were selected from the 384 provided by (Guo and Li, 2020). The representative colors of the 24 solar terms were used to build a color sample library, and four colors were selected for each solar term to get 24 × 4 = 96 colors. In addition, white, gray, and black were also studied. As shown in Figure 2, a total of 99 colors formed the final color database, defined as C = (C1, C2, ..., C99). The conversion of colors to the Munsell color system based on hue, value, and chroma is decoded as “hue value/chroma.”

4. Quantification of color aesthetics of cultural and creative products

4.1. Color image

4.1.1. Description and evaluation of color image semantics

Kansei Engineering designs products by analyzing people’s sensibility and manufactures products based on human preferences. Collecting and extracting perceptual image vocabulary is an important basis for establishing imagery space and gaining a deeper understanding of how users feel about products. Therefore, the first task is to filter and select the image vocabulary. People’s perceptual cognition and visual feelings aroused by the color of cultural and creative products can be described by the semantic vocabulary of perceptual image. An appropriate semantic vocabulary can improve the accuracy of the experiment. Therefore, it is necessary to collect a vocabulary to describe the colors of cultural and creative products by means of references, expert interviews, questionnaires, and so on (Kapkin and Joines, 2018). The present study collected 74 image vocabularies from the three levels of surface meaning, behavioral meaning, and spiritual meaning, and then obtained the top 30 words with the highest votes through a questionnaire survey to form a semantic set of perceptual image (see Table 1), where the set K = (K1 Modern, K2 Technological, K3 Trendy......Kn Female).

Secondly, the color samples in Figure 2 were taken as independent variables, and people’s subjective feelings about the color design features were taken as dependent variables. A semantic difference method was used to design a questionnaire that measures emotional tendency on a five-point Likert scale. The questionnaire conformed to the ethical principles of the declaration of Helsinki. Each participant was given a brief introduction and signed an informed consent. The 99 color samples were combined with the 30-piece semantic vocabulary. Respondents scored the semantic vocabulary according to their subjective
feelings after viewing the color samples. The scores consisted of five options, 1–5, indicating the degree of agreement between the respondents’ feelings and the semantic vocabularies, where 1 indicates strong disagreement, 2 indicates mild disagreement, 3 indicates a neutral attitude, 4 indicates mild agreement, and 5 indicates strong agreement.

Table 1. Image vocabularies.

|   | Modern | Classic | Attractive | Vivacious | Safe |
|---|--------|---------|-----------|-----------|------|
| 1 | Modern | Tasteful | Attractive | Vivacious | Safe |
| 2 | Trendy  | Traditional | Modern | Vivacious | Safe |
| 3 | Futuristic | Unique | Vivacious | Vivacious | Safe |
| 4 | Elegant | Personalized | Vivacious | Vivacious | Safe |
| 5 | Interesting | Vivacious | Vivacious | Vivacious | Safe |
| 6 | Dazzling | Vivacious | Vivacious | Vivacious | Safe |

Figure 2. Color samples.
4.1.2. Factor analysis of color image semantics

To investigate the relationship between the color samples and the color image semantic vocabulary, factor analysis was used to group the components of the semantic vocabulary. Factor analysis took the minimum information loss as the objective and synthesized numerous original variables into several comprehensive indicators, which we call factors.

The subjects evaluated 30 kinds of image perception of the 99 color samples. The magnitude values were set between 1 and 5, with larger values indicating a sense of closeness to the feeling described by the image vocabulary. Based on the scores of all questionnaire data, factor analysis was performed using the SPSS software for dimensionality reduction. The analysis results revealed correlations among the components of the semantic vocabulary.

The Kaiser–Meyer–Olkin (KMO) test was used to investigate the partial correlations among the semantic vocabulary. A KMO value of 0.836 was calculated; as this is greater than 0.7, these correlations could be used for factor analysis. The observed value of the Bartlett test of sphericity statistic was 3435.914 and the significance was about 0.000; as this is less than 0.01, there is a significant correlation among the 30 semantic vocabulary terms. Using principal component analysis, the values with eigenvalues greater than one were extracted as factors. The varimax was used to rotate the factors. Six perceptual image semantic factors were extracted. As shown in Table 2, the cumulative variance contribution rate of these six factors is 82.334%.

The rotated factor load matrix was then obtained. The perceptual image vocabularies represented by the data in bold in each column in Table 3 have high loads on the factors corresponding to each column. The factor loads refer to the correlation coefficients between the 30 image vocabulary components and the common factors, and larger absolute values indicate a closer relationship with the common factors. The first factor mainly explains nine image vocabulary terms, such as auspicious and warm, which mainly reflect the users’ intuitive feelings towards the color of cultural and creative products. The second factor primarily explains ten image vocabulary terms, such as solemn and classic, which mainly show that users believe the color of cultural and creative products should be traditional and classical, reflecting solemn and elegant aesthetic requirements. The third factor mainly explains nine image vocabulary terms, such as attractive and touching, which mainly reflect that users prefer attractive and interesting color matching. The fifth factor mainly explains the two image vocabulary terms of natural and harmony, reflecting the natural and harmonious design style. The sixth factor mainly explains the term safe, which reflects the need for security brought about by color.

Therefore, based on the rotated factor load matrix, six common factors were extracted: Factor 1—warm and auspicious, Factor 2—classic and solemn, Factor 3—fashion trend, Factor 4—moving and interesting, Factor 5—natural and harmony, and Factor 6—safe and stable.

The Monte Carlo PCA for parallel analysis program developed by Watkins was used for parallel analysis to verify the number of factors (Watkins, 2000). Based on the principal component method, 500 random data were generated using the Monte Carlo technique, and the average eigenvalues were obtained and compared with the real data from the SPSS factor analysis (Figure 3). The results showed that the eigenvalue

| Component | Initial Eigenvalues | Extraction Sums of Squared Loadings | Rotation Sums of Squared Loadings |
|-----------|---------------------|------------------------------------|----------------------------------|
| Total     | % of Variance       | % of Variance                      | % of Variance                     |
| Total     |                     | Total % of Variance                | Cumulative %                      |
| 1         | 9.791               | 32.638                             | 32.638                            |
| 2         | 5.260               | 17.533                             | 50.170                            |
| 3         | 4.583               | 15.278                             | 65.448                            |
| 4         | 2.054               | 6.845                              | 72.293                            |
| 5         | 1.710               | 5.699                              | 77.993                            |
| 6         | 1.303               | 4.342                              | 82.334                            |
| 7         | 0.784               | 2.613                              | 84.947                            |
| 8         | 0.636               | 2.120                              | 87.067                            |
| 9         | 0.540               | 1.801                              | 88.868                            |
| 10        | 0.421               | 1.403                              | 90.271                            |
| 11        | 0.415               | 1.384                              | 91.655                            |
| 12        | 0.355               | 1.183                              | 92.838                            |
| 13        | 0.335               | 1.116                              | 93.954                            |
| 14        | 0.267               | 0.889                              | 94.843                            |
| 15        | 0.212               | 0.707                              | 95.550                            |
| 16        | 0.188               | 0.628                              | 96.176                            |
| 17        | 0.172               | 0.573                              | 96.751                            |
| 18        | 0.155               | 0.516                              | 97.268                            |
| 19        | 0.120               | 0.400                              | 97.668                            |
| 20        | 0.104               | 0.348                              | 98.016                            |
| 21        | 0.102               | 0.339                              | 98.355                            |
| 22        | 0.086               | 0.287                              | 98.642                            |
| 23        | 0.084               | 0.279                              | 98.921                            |
| 24        | 0.071               | 0.238                              | 99.159                            |
| 25        | 0.065               | 0.216                              | 99.375                            |
| 26        | 0.050               | 0.166                              | 99.541                            |
| 27        | 0.043               | 0.143                              | 99.683                            |
| 28        | 0.037               | 0.124                              | 99.807                            |
| 29        | 0.030               | 0.098                              | 99.906                            |
| 30        | 0.028               | 0.094                              | 100.000                           |
curves of the real data intersected with those of the simulated data between the 5th and 7th factors, indicating that the variation explained by the first six factors was significantly different from that caused by random errors and that six factors should be extracted.

4.2. Visual aesthetics

4.2.1. Harmony

Two or more colors can be combined uniformly and harmoniously according to certain methods to achieve visual harmony and psychological balance, known as color harmony. Munsell’s color harmony theory holds that color harmony is a color order, and the series of hue, value, and chroma of a color solid can be arranged and made in a certain order (Moon and Spencer, 1944). In a color solid, any straight line, circle, ellipse, spiral, and so on is directional, and the selected color matching is harmonious. After establishing a color or group of colors, the corresponding harmonic colors can be obtained from the color solid. According to the viewpoint that “beauty lies in the unity of diversity,” the German mathematician Birkhoff proposed the following mathematical model to express formal beauty through color harmony (Birkhoff, 1933), as shown in Eq. (1):

\[ M = \frac{O_r}{C_o} \] (1)

where \( M \) represents the aesthetics of color harmony, \( O_r \) represents the element of order, and \( C_o \) represents the element of complexity.

The element of complexity \( C_o \) can be expressed as Eq. (2):

\[ C_o = C_n + C_h + C_v + C_c \] (2)

where \( C_n \) represents the total number of colors in the color matching, \( C_h \) represents the number of color pairs with a hue difference among all possible two-color combinations, \( C_v \) represents the number of color pairs with a value difference among all possible two-color combinations, and \( C_c \) represents the number of color pairs with a chroma difference among all possible two-color combinations.

As shown in Eq. (3), the element of order \( O_r \) includes two conditions: achromatic color and chromatic color. The values of the element of order are listed in Table 4.

Table 3. Rotated component matrix.

| Component       | 1     | 2     | 3     | 4     | 5     | 6     |
|-----------------|-------|-------|-------|-------|-------|-------|
| image 28        | 0.928 | 0.080 | -0.083| 0.075 | -0.080| 0.073 |
| image 22        | 0.087 | -0.064| -0.087| 0.200 | 0.086 | 0.069 |
| image 20        | 0.885 | 0.208 | 0.135 | -0.029| -0.108| 0.111 |
| image 18        | 0.879 | -0.390| 0.091 | 0.110 | 0.145 | -0.009|
| image 24        | -0.065| 0.271 | 0.103 | -0.126| 0.061 | 0.105 |
| image 26        | 0.859 | 0.095 | 0.361 | -0.044| 0.064 | -0.047|
| image 21        | 0.826 | -0.267| -0.143| 0.190 | -0.074| -0.010|
| image 29        | -0.772| 0.348 | -0.064| 0.079 | 0.189 | 0.303 |
| image 27        | 0.675 | -0.496| 0.295 | 0.112 | 0.206 | -0.133|
| image 10        | -0.157| 0.884 | -0.201| -0.036| 0.092 | 0.083 |
| image 17        | -0.040| 0.802 | 0.184 | 0.069 | 0.073 | -0.131|
| image 11        | -0.096| 0.770 | -0.304| 0.152 | 0.304 | 0.013 |
| image 12        | -0.341| 0.766 | -0.207| 0.329 | -0.029| -0.087|
| image 16        | -0.125| 0.743 | -0.145| 0.208 | 0.202 | 0.015 |
| image 25        | -0.489| 0.678 | -0.186| -0.051| -0.035| 0.196 |
| image 23        | 0.416 | 0.640 | -0.122| 0.072 | 0.119 | 0.040 |
| image 22        | -0.357| 0.628 | 0.061 | 0.485 | -0.123| -0.013|
| image 21        | 0.280 | 0.621 | 0.015 | -0.162| -0.045| 0.386 |
| image 18        | 0.423 | -0.587| -0.024| 0.247 | 0.098 | 0.293 |
| image 17        | -0.060| -0.068| 0.954 | 0.092 | 0.063 | 0.038 |
| image 16        | 0.046 | -0.129| 0.952 | 0.142 | -0.013| 0.049 |
| image 15        | 0.037 | -0.139| 0.951 | 0.130 | 0.011 | 0.060 |
| image 14        | 0.028 | -0.087| 0.946 | 0.157 | -0.015| -0.002|
| image 13        | 0.417 | -0.430| 0.485 | 0.076 | 0.341 | -0.313|
| image 12        | 0.262 | 0.060 | 0.247 | 0.852 | 0.040 | 0.166 |
| image 11        | 0.289 | -0.004| 0.291 | 0.799 | 0.077 | 0.066 |
| image 10        | 0.056 | 0.232 | 0.086 | 0.771 | 0.191 | -0.026|
| image 9         | -0.002| 0.125 | 0.048 | 0.045 | 0.912 | -0.077|
| image 8         | -0.060| 0.173 | 0.015 | 0.179 | 0.858 | 0.165 |
| image 7         | -0.094| -0.016| 0.111 | 0.147 | 0.060 | 0.890 |

Figure 3. Scree plot.
Oc = \left\{ \begin{array}{ll} \sum O_8 & (\text{for achromatic color}) \\
\sum O_8 + O_r + O_v & (\text{for chromatic color}) \end{array} \right.

where \(O_8\) represents the element of order for achromatic colors; \(O_r\), \(O_v\), and \(O_c\) represent the elements of order for chromatic colors, given by the hue difference, value difference, or chroma difference, respectively.

The harmonic and disharmonic ranges of any two colors are presented in Table 5. Each comparison contains three regions. One hundred equal parts of the hue ring are divided into five regions, and the hue interval determines the \(O_h\) value. The value interval is divided into six regions and determines the \(O_v\) value. The chroma interval is divided into five regions and determines the \(O_c\) value.

According to the above formulae, the harmonious aesthetics of product color matching were calculated. When \(M > 0.5\), the color matching of the product is considered to be beautiful and to conform to the law of color harmony.

4.2.2. Balance

When two or more colors exist in a common range, there must be a color area proportion relationship between them. Generally, the area with a high chroma and a high value will be relatively large. Colors with a low value make people feel heavy, whereas colors with a high value make people feel light (Hsiao et al., 2017). The balance of color is affected by the joint action of the color area and value, giving the color a dynamic balance (i.e., a sense of movement, tension, pressure) and a static balance (i.e., a sense of stability, calm). The front of the product best reflects its morphological characteristics and color aesthetics, and is the best side to convey information. Therefore, this study considers the front of the product as the research object when studying the balance of color. According to Eqs. (4), (5), (6), and (7), the balance of color is a combination of the horizontal balance \(B_x\) and vertical balance \(B_y\) based on the following calculations:

\[ B = 1 - \frac{B_x + B_y}{2} \]  
\[ B_x = \frac{|w_L - w_R|}{\max(w_L, w_R)} \]  
\[ B_y = \frac{|w_U - w_D|}{\max(w_U, w_D)} \]  
\[ w_i = \sum_{j=1}^{n} v_{ij}d_{ij} \]

where \(B, B_x, \) and \(B_y\) represent balance, horizontal balance, and vertical balance, respectively; \(w_L\) and \(w_R\) represent the area moment of the color value on the left and right sides of the y-axis, respectively; \(w_U\) and \(w_D\) represent the area moment of the color value above and below the x-axis, respectively; \(L, R, U, \) and \(B\) represent the left, right, upper, and lower regions, respectively; \(v_{ij}\) represents the value of color \(j\) in region \(i\); \(d_{ij}\) represents the distance from the centroid of color \(j\) in region \(i\) to the y-axis or x-axis; and \(n\) represents the number of colors involved in the cultural and creative product color matching.

**Table 5. Color interval division.**

| Harmonic range | Disharmonic range | Only hue changes | Only value changes | Only chroma changes |
|----------------|-------------------|-----------------|-------------------|-------------------|
| Identity       | 0-1j.n,d          | 0-1j.n.d        | 0-1j.n.d          |
| First ambiguity| 1j.n.d-7          | 1j.n.d-0.5      | 1j.n.d-3          |
| Similarity     | 7-12              | 0.5-1.5         | 3-5               |
| Second ambiguity| 12-28             | 1.5-2.5         | 5-7               |
| Contrast       | 28-50             | 2.5-10          | >7                |
| Glare          | —                 | >10             | —                 |

4.2.3. Symmetry

Information entropy is a concept borrowed from thermodynamics to measure the uncertainty of a random event or the amount of information, effectively providing a quantitative measurement. The more orderly a system is, the lower the information entropy is; conversely, the more chaotic a system is, the higher the information entropy is. Therefore, information entropy can also be said to measure the degree of orderliness of a system (Jia and Zhang, 2014). This study uses “entropy” to describe the orderliness of the product color area distribution, that is, whether the color area distribution conforms to symmetrical aesthetics (Deng et al., 2021). Symmetry makes people feel stable and solemn. The front of the product can be partitioned into four parts: upper left, upper right, lower left, and lower right. Suppose \(n\) colors are used for the color matching design, and the pixel value of each color area can be calculated by image processing software. If the area (pixel value) of one color is the same in the four areas, the entropy \(E\) of the color attains its maximum, which can be expressed as Eq. (8).

\[ E = D(E_1, E_2, E_3, E_4) = -k \sum_{i=1}^{4} E_i \ln E_i \]  

where \(k = \frac{1}{\ln n}, E_i = \frac{A_{color}}{A_i}, A_{color} = \sum A_j, \) and \(j = UL, UR, LL, LR.\)

Here, \(A_j\) indicates the area of a certain color in region \(j\) and \(A_{color}\) denotes the total area of a certain color on the front of the product.

If the area of each color is equal on all four sides of the product, the color distribution \(D\) attains its maximum value, as shown in Eq. (9).

\[ D = \frac{\sum_{i=1}^{n} E_i}{n} \]

5. Interactive genetic color matching based on grayscale for interval fitness value

IGAs combine artificial evaluation and evolutionary computation to achieve guidance of an evolutionary process through human-computer interaction, breaking through the limitations of explicit performance metrics used in traditional algorithms (Cai, 2020). To solve the problem of evaluation noise caused by user fatigue, this paper proposes a fitness value composed of subjective image evaluation and an objective visual aesthetics value. The objective visual aesthetics value is calculated according to the formulae in Section 4.2. The subjective image evaluation reflects people’s intuitive feelings in the process of interactive evaluation.

**Table 4. Elements of order.**

| Order relationship | Harmonic relationship |
|--------------------|----------------------|
|                    | Identity First ambiguity Similarity Second ambiguity Contrast Glare |
| \(O_8\)            | +1.5 0 +1.1 +0.65 +1.7 | |
| \(O_1\)            | -1.3 -1 +0.7 -0.2 +3.7 +0.2 |
| \(O_2\)            | +0.8 0 +0.1 0 +0.4 |
| \(O_3\)            | +1  | |
Faced with the color matching design of cultural and creative products, people's cognition may be uncertain, making the subjective image evaluation fuzzy. Therefore, according to the grey system theory, the subjective image evaluation process is defined as a grey system (Deng, 1982). To improve the accuracy of human evaluation and reflect people's cognition of the evaluation objects, we use a grayscale to measure the uncertainty of the subjective evaluation of individual fitness values, based on the method proposed by Guo and He (2009). The grayscale is used to design adaptive crossover and mutation probabilities, which accelerate the evolution process and improve algorithm performance (Guo and Wang, 2011).

5.1. Fitness

The ith evolutionary individual (color scheme) in the evolutionary population x(t) of generation t is set as x_i(t), i = 1, 2, ..., n, where n is the size of the population. People's cognition of color scheme x_i(t) is fuzzy, so the subjective fitness value f(x_i(t)) of color scheme x_i(t) can be expressed as an interval, as shown in Eq. (10):

\[ f(x_i(t)) = [f_1(x_i(t)), f_2(x_i(t))] \] (10)

The width of this interval is defined in Eq. (11):

\[ w(f(x_i(t))) = f_2(x_i(t)) - f_1(x_i(t)) \] (11)

where \( f_1(x_i(t)) \) and \( f_2(x_i(t)) \) represent the upper and lower limits of the evaluation of color scheme x_i(t), respectively.

The objective fitness value a(x_i(t)) of color scheme x_i(t) can be expressed as Eq. (12):

\[ a(x_i(t)) = M(x_i(t)) + B(x_i(t)) + D(x_i(t)) \] (12)

where \( M(x_i(t)) \), \( B(x_i(t)) \), and \( D(x_i(t)) \) represent the evaluation of the harmony, balance, and symmetry of color scheme x_i(t), respectively.

The overall fitness function is composed of subjective and objective parts, and is expressed as Eq. (13):

\[ F(x_i(t)) = a(x_i(t)) + \alpha a(x_i(t)) \] (13)

where \( \alpha \) and \( \beta \) represent the weights of the subjective image evaluation and the objective aesthetics calculation value, respectively; \( \alpha + \beta = 1 \).

5.2. Grayscale of individual fitness value

Because people's subjective evaluation of color scheme x_i(t) is uncertain, it is difficult to give an accurate evaluation value. Thus, \( f(x_i(t)) \) is an uncertain number, and the real subjective fitness value (satisfactory solution) \( f'(x_i(t)) \) of color scheme x_i(t) could be considered as a measured gray number. When an interval number is used to describe the individual fitness value, the lower limit \( f_1(x_i(t)) \) and upper limit \( f_2(x_i(t)) \) of the measured fitness value of the evolutionary individual become cognitive data reflecting the preference, constituting the whitening number of \( f'(x_i(t)) \). The bounded continuous closed interval \( f(x_i(t)) = [f_1(x_i(t)), f_2(x_i(t))] \) becomes the numerical coverage of the gray number \( f'(x_i(t)) \), and \( f'(x_i(t)) \) is the continuously measured gray number.

The interval number \( f(x_i(t)) \) is the set of all whitening numbers \( f'(x_i(t)) \). In the interval \( f(x_i(t)) \), there must be a unique real value reflecting the subjective evaluation of the individual, that is, the real subjective fitness \( f'(x_i(t)) \) of color scheme x_i(t) must be in the interval \( [f_1(x_i(t)), f_2(x_i(t))] \). If the grayscale of \( f'(x_i(t)) \) is \( g(x_i(t)) \), the grayscale formula is defined in Eq. (14):

\[ g(x_i(t)) = \frac{a_1(x_i(t)) + \beta a(x_i(t))}{a_2(x_i(t)) + \beta a(x_i(t))} \] (14)

The population evolution grayscale of the current evolutionary generation t is calculated according to Eq. (15):

\[ g(t) = \frac{1}{n} \sum_{t=1}^{\text{nt}} g(x_i(t)) \] (15)

The grayscale \( g(x_i(t)) \) reflects the uncertainty of people's evaluation of the color scheme. In the early stages of evolution, people's cognition of color scheme x_i(t) is fuzzy, the uncertainty of the evaluation is large, \( w(f'(x_i(t))) \) is large, the whiteness number in \( f(x_i(t)) \) is large, and the grayscale \( g(x_i(t)) \) is large. As the population evolves continually, people's cognition of color scheme x_i(t) becomes increasingly clear, and the uncertainty of the evaluation gradually decreases. Thus, the whiteness number in \( f(x_i(t)) \) decreases, the grayscale decreases gradually, and \( w(f'(x_i(t))) \) becomes narrower. However, when an evaluation degenerates to a single value, the individual fitness value remains uncertain under the influence of noise, although there is only one whitening number of \( f'(x_i(t)) \). At this time, the individual fitness value could be regarded as a discrete measured gray number with a grayscale of 0.

The grayscale provides an objective means of measuring the uncertainty in the subjective evaluation of individual fitness values. This essentially reflects the fuzziness and progressiveness of people's cognition of evaluation objects.

5.3. Adaptive crossover and mutation mechanisms

5.3.1. Adaptive crossover probability

The crossover operation is the main method whereby new individuals are generated. The adaptation of the crossover probability is reflected in the following two aspects. First, if the ratio of the grayscale of evolutionary individuals to the grayscale of the population is large, the uncertainty of the fitness value of the individual is large. At this time, the crossover probability of the individual is relatively high; otherwise, the crossover probability is relatively low. Second, with the process of evolution, the uncertainty of the evaluation gradually decreases, and the gap between the grayscale of evolutionary individuals and the grayscale of the population will continue to decrease. To ensure that the algorithm converges, the crossover probability of evolutionary individuals should decrease as the evolutionary algebra increases. Thus, the crossover probability \( p_c(x_i(t)) \) of evolutionary individual x_i(t) is set as follows:

\[ p_c(x_i(t)) = 1 / (1 + e^{-k_1 f(x_i(t))}) \] (16)

where \( T \) is the evolutionary termination algebra and \( k_1 \) is a coefficient.

Consider the parent individuals x_i(t) and x_j(t). The crossover probabilities \( p_c(x_i(t)) \) and \( p_c(x_j(t)) \) are calculated based on Eq. (16) before the crossover operation, and then the larger value is taken as the crossover probability of the two individuals. The crossover operation is then applied.

5.3.2. Adaptive mutation probability

The local search ability is improved by the mutation operation, which can accelerate convergence to the optimal solution and has the effect of maintaining population diversity and preventing premature convergence. The adaptation of the mutation probability is reflected in the following two aspects. First, if the ratio of the grayscale of the population to the grayscale of evolutionary individuals is small, the uncertainty of the individual fitness value is large. At this time, each individual's mutation probability is relatively high; otherwise, the mutation probability is relatively low. Second, in the later stages of evolution, the mutation probability of evolutionary individuals should be reduced to ensure algorithm convergence with increasing evolutionary algebra. Therefore, the mutation probability is limited to the range (0, 0.5). The mutation probability \( p_m(x_i(t)) \) of evolutionary individual x_i(t) is set as follows:
5.4. Steps of the color matching algorithm

As shown in Figure 4, the steps of the IGA based on the grayscale for interval fitness are as follows.

Step 1. Set the control parameters of population evolution, set \( t = 0 \), and initialize the evolutionary population \( x(t) \).

Step 2. Evaluate an evolutionary individual, give the individual's interval fitness value, and calculate the overall fitness value according to Eq. (13).

Step 3. Calculate the grayscale of the fitness value using Eqs. (14) and (15).

Step 4. Perform roulette selection to generate the parent population.

Step 5. Conduct crossover and mutation operations using Eqs. (16) and (17) to generate the offspring evolutionary population \( x(t) \); set \( t = t + 1 \).

Step 6. Judge whether the evolutionary termination condition of the population is satisfied. If yes, proceed to Step 7; otherwise, return to Step 2.

Step 7. Output the optimal evolutionary individual.

6. Example verification

The interactive genetic color matching method was applied to speaker box color design to verify its feasibility. The speaker box design took “high mountains and flowing water” as the theme, its “shape” was reflected in the appearance, and its “meaning” was embodied in the emotional element of companionship. Through the detailed design of the decorative line, hole shape, lighting, and so on, a picture and artistic conception of “high mountains and flowing water” were developed. This gave the speaker box a certain aesthetic feeling and cultural charm, so that users seemed to be in the mountains and rivers when enjoying music.

To design a color scheme that conforms to the above description, this study identified individuals with high fitness values in the color scheme population to obtain satisfactory results for users. First, the initial population was generated based on the user-specified target product and selected color semantic vocabulary. Then, the individual fitness values were obtained by combining subjective image evaluation with objective visual aesthetics values, and a conditional judgment was applied: if the requirements were met, the color matching scheme was output; on the contrary, the individuals with the best fitness values in each generation of the population were directly saved to the next generation, and other individuals were subjected to selection, crossover, and mutation operations to make the population evolve. When the fitness of a color scheme exceeded the set threshold or the user achieved a satisfactory result in the operation process, the genetic process was terminated and the color scheme was output.

6.1. Genetic operation of color matching

6.1.1. Coding

Coding is not only the basis of the genetic optimization of color matching, but also the basic element for expressing the color matching style of products. Before the genetic manipulation of color matching, the product was divided into different color matching components. Colors that remained unchanged through the process of genetic operations were called static attributes; the colors corresponding to each color matching part that were continuously iterated and updated were called dynamic attributes.

The traditional Chinese color database was coded. Each color scheme \( S_1 \) represents a chromosome, defined as \( \{x_1, x_2, \ldots, x_m\} \), where \( m \) is the total number of colors. The composition of the chromosome is shown in Figure 5(a). A gene represents a color \( x_m \). As shown in Figure 5(b), the first digit represents the solar term number \( p_i \) and the second digit represents the color sample number \( q_i \) in the solar term \( p_i \). The maximum number of solar terms is 24 and the maximum number of color samples is four. The chromosome code in Figure 5(c) indicates that the color scheme has two colors. The first color is No. 2 in solar term 5 and the second color is No. 4 in solar term 9.

The chromosomes needed to be decoded to achieve the mapping from genotype to phenotype. For example, the color values corresponding to the chromosomes in Figure 4(c) can be queried from Figure 2. The RGB values of \( Z_{5,2} \) are \( \{R138, G24, B116\} \), and the RGB values of \( Z_{9,4} \) are \( \{R46, G144, B93\} \). In this way, the two colors can be assigned to predefined areas of the target product for image evaluation by the designers or users.

6.1.2. Selection

After the evaluator had given a fitness value to an individual, the proportion of each individual's fitness in the total population fitness was
calculated, and the individuals with high fitness values were passed to the next-generation population by the roulette method (X. Zhu et al., 2020).

### 6.1.3. Crossover

Two parent individuals were selected according to a certain probability to generate two sub-individuals. The single-point crossover operation was carried out, and two genes from the previous generation were selected according to the crossover probability to produce two genes for the next generation.

### 6.1.4. Mutation

To avoid becoming trapped around a local optimum solution during optimization, a single-point mutation was used to generate a new chromosome. A locus in the gene sequence was randomly selected for mutation and replaced by the remaining available values of that locus, thus generating offspring individuals.

### 6.2. Interactive evaluation process

Using Visual Studio, a prototype system for color matching design was developed. The interactive genetic color matching interface for cultural and creative products is shown in Figure 6. Each population has six individuals (color scheme). In the specific operation, we first set the weights of subjective image evaluation and objective visual aesthetics. When users have a rich color matching experience, they assign a larger weight to subjective image evaluation to fully reflect the personalization of the design results; on the contrary, the weight of objective visual aesthetics can be increased to make full use of expert knowledge in achieving reasonable design results. Clicking the “Start” button generates the initial population for color matching. The user drags the slider to score each color scheme interactively or inputs the lower and upper limits of the evaluation value. When the “Next generation” button is clicked, the system performs genetic evolution of the color scheme based on the user’s evaluation.

Table 6. Performance analysis of the algorithm (The participants with design education background).

| Participants | Evolutionary algebra/number of satisfactory solutions | Proposed method | General IGA |
|--------------|------------------------------------------------------|-----------------|-------------|
|              |                                                      | 1   | 2     | 3   | 4   | 5   | 6   |    |        |
| ID1          | 16                                                   | 38  | 14   | 26  | 14  | 27  | 15  | 29  | 15  | 30  | 16  | 31  | 16  | 29 |
| ID2          | 15                                                   | 32  | 15   | 28  | 14  | 27  | 15  | 27  | 16  | 30  | 16  | 32  | 17  | 30 |
| ID3          | 16                                                   | 37  | 15   | 27  | 15  | 28  | 15  | 28  | 16  | 28  | 17  | 33  | 17  | 32 |
| ID4          | 14                                                   | 36  | 14   | 28  | 15  | 27  | 16  | 30  | 16  | 27  | 16  | 30  | 18  | 35 |
| ID5          | 15                                                   | 38  | 14   | 26  | 15  | 28  | 15  | 26  | 17  | 32  | 17  | 32  | 20  | 36 |
| ID6          | 15                                                   | 37  | 14   | 26  | 14  | 26  | 16  | 31  | 17  | 30  | 17  | 29  | 17  | 30 |
| Mean value   | 15.17                                                | 36.33| 26.83| 14.50| 27.17| 15.33| 28.50| 16.17| 29.50| 16.50| 31.17| 17.50| 32.00|
down. This increased the number of generations required, which abilities increased, the convergence speed of the general IGA slowed mutation probabilities were small. As the crossover and mutation prob-

value of the evolutionary algebra was small when the crossover and the general IGA was prone to premature convergence and the average number of generations $T$

product color matching, and can quickly establish the mapping between that industrial design students are familiar with the image cognition of factory solutions found in the run, as shown in Tables 6 and 7. The proposed method was compared with a general IGA by counting the other half were non-industrial design students (ND1-ND6). The participate in a test. Half were industrial design students (ID1-ID6) and 6.3. Analysis of color matching results 6.3.1. Evolutionary effect analysis Twelve college students (six male and six female) were recruited to participate in a test. Half were industrial design students (ID1-ID6) and the other half were non-industrial design students (ND1-ND6). The proposed method was compared with a general IGA by counting the termination algebra of population evolution and the number of satisfactory solutions found in the run, as shown in Tables 6 and 7. The general IGA uses six different crossover and mutation probabilities (see Table 8). In the adaptive crossover probability calculation formula and adaptive mutation probability calculation formula of this method (i.e., Eqs. (16) and (17)), $k_1 = k_2 = 0.1$, $\alpha = 0.6$, $\beta = 0.4$, and the maximum number of generations $T = 20$.

Both students with and without a background in design education, the general IGA was prone to premature convergence and the average value of the evolutionary algebra was small when the crossover and mutation probabilities were small. As the crossover and mutation probabilities increased, the convergence speed of the general IGA slowed down. This increased the number of generations required, which enhanced the evaluation burden of humans and led to fatigue.

Using the interval fitness values, the average evolutionary algebra did not decrease significantly overall, but more satisfactory solutions were found by the participants compared with the general IGA. This shows that the optimization efficiency of the algorithm can be improved by using a grayscale to design adaptive crossover and mutation probabilities, which conform to the human cognitive process.

Comparing the average evolutionary algebra and satisfactory solutions in Tables 6 and 7, for the method proposed in this paper, the average evolutionary algebra evaluated by non-industrial design students is three generations more than that of industrial design students, and the difference in the number of satisfactory solutions is not significant. It shows that this method has a positive effect on participants without product color matching design knowledge and improves the evolutionary efficiency. For participants without a design education background, the convergence of interactive genetic color matching can be further improved by increasing the value of $\beta$ and decreasing the value of $\alpha$.

6.3.2. Partial color schemes and verification Partial satisfactory solutions found during the tests are shown in Figures 7 and 8. During the evolution process, different user evaluations affected the evolution direction of the color schemes, producing different color matching results. As shown in Figure 7, taking “classic and solemn” as the target image gives stable and elegant evolution results. As shown in Figure 8, modern and fashionable evolution results can be obtained by taking “fashion trend” as the target image. The designers can further refine the design on this basis.

In Table 9, J1–J5 represent the color scheme of the target image “classic and solemn,” and S1–S5 represent the color scheme of the target image “fashion trend.” From the perspective of aesthetic principles, the objective evaluation of schemes J5 and S3 are not high, but they are still regarded as satisfactory solutions after integrating the users’ subjective image evaluation. This shows that the proposed method reflects users’ preferences and enhances the satisfaction of users’ perceptual needs.

To verify the effectiveness of the proposed method, the color schemes generated by the system were evaluated in the form of questionnaire. Forty subjects were invited to evaluate the five color schemes of “fashion trend” on the same display device. The results of statistical analysis are shown in Figure 9. The abscissa represents the image score of the color scheme. The higher the score, the more the subjects think the color scheme matches the target image. The ordinate represents the number of subjects.

As can be seen from Figure 9, most of the evaluations are between 3 and 5 points, and 4 points are the most. For example, for scheme S5, there are 1 evaluator with 2 points, 6 evaluators with 3 points, 30 evaluators with 4 points, and 3 evaluators with 5 points. Table 10 shows the average score of the color schemes. It can be seen that all the average scores are

![Figure 7](image-url) Evolution results from “classic and solemn” target image.
about 4 points. The evaluation result of the questionnaire is consistent with the fitness value obtained by the interactive evolution system. This result shows that users are satisfied with the color schemes derived from the interactive genetic color matching system, which proves that the system can quickly and accurately provide color schemes that meet users’ emotional image preferences.

7. Discussion and limitations

This paper focuses on aiding color matching design, which is one of the most common needs of designers. Integrating the product color design process with computer science and developing color matching tools can help designers with some color designs that need to reproduce cultural images, and reduce the dependence on the designer’s individual talent. It also improves the efficiency of color matching design and allows for the batch generation of color schemes.

IGAs make use of the global optimization characteristics of genetic algorithms and allow users to evaluate the evolutionary results. They integrate users’ perceptual needs into computer technology, ensuring that the resulting scheme is aimed at users’ needs. The system incorporates the user as a key participant in the design process and also provides multiple color schemes for designers to choose from and make decisions. The system provides designers with inspiration, shortens design time, and offers innovative design capabilities. During system operation, $\alpha$ and $\beta$ are the weights of subjective image evaluation value and objective visual aesthetics calculation value, respectively, which are related to the situation of the decision-maker. If the decision-maker has a design-related background (belongs to the expert user) or wants the final scheme to match more with the personal preference of the decision-maker, the $\alpha$ value can be obtained larger, $\alpha>\beta$, and both satisfy the relationship equation: $\alpha+\beta = 1$.

We implemented semantic difference experiments to determine users’ color image. To better match oriental aesthetics and Chinese aesthetic contexts, we used traditional Chinese colors to create color samples. In ancient China, the year was divided into solar terms based on climate. The 24 solar terms accurately reflect the natural rhythmic changes. Guo and Li (2020) extracted colors from each solar term to build the traditional Chinese colors, a total of 384. If we select 384 color samples, then the evaluator needs to perform $384 \times 30$ evaluations, which is too heavy a burden for the evaluator. Thus, only four representative colors were selected for each solar term in this experiment. And these 30 image vocabularies were collected through references, expert interviews, questionnaires, etc. In the future, we can consider the way of big data web crawler to obtain the hot words. However, there are still some deficiencies in this study.

(1) Considering the influence of hue, value, chroma, color type, area, and position distribution on the color matching effect, color quantization was carried out from the three aspects of color harmony, balance, and symmetry. The psychological feeling given by color is perceptually quantified, and the color aesthetics are evaluated using a multi-factorial index. This paper has achieved the quantification of visual aesthetics to a certain extent, but the effect is not comprehensive.

(2) To solve the problem of uncertainty and fatigue of user evaluation in the IGA process, the grayscale of the interval fitness value was introduced, and adaptive crossover and mutation probabilities were designed based on the grayscale of fitness. For an individual with a larger grayscale, the probability of crossover and mutation is greater. $k_1$ and $k_2$ are the adjustment coefficients of the adaptive

\begin{table}
\centering
\caption{Evaluation data of color scheme.}
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|}
\hline
Number & Color 1 & Color 2 & Subjective image evaluation & Objective aesthetics evaluation \\
 & RGB values & H V/C values & RGB values & H V/C values & Lower limit & Upper limit & Harmony & Balance & Symmetry \\
\hline J1 & 166,126,183 & 5.5P 5.8/8.4 & 255,251,199 & 9.7Y 9.8/3 & 0.7 & 0.75 & 0.89 & 0.53 & 0.68 \\
J2 & 191,192,150 & 1.3GY 7.6/2.8 & 129,157,142 & 5.2G 6.1/2.2 & 0.75 & 0.8 & 0.74 & 0.74 & 0.68 \\
J3 & 119,138,119 & 0.5G 5.4/2.1 & 223,214,184 & 4.6Y 8.5/2 & 0.7 & 0.75 & 0.89 & 0.53 & 0.68 \\
J4 & 236,176,193 & 5.8R P 7.7/6 & 220,199,225 & 6.4P 8.2/4.2 & 0.7 & 0.75 & 0.36 & 0.83 & 0.68 \\
J5 & 235,238,232 & 7.3GY 9.4/0.4 & 226,162,172 & 8.9 R P 7.2/6.1 & 0.7 & 0.75 & 0.89 & 0.53 & 0.68 \\
\hline
\end{tabular}
\end{table}

Figure 8. Evolution results from “fashion trend” target image.

Figure 9. Questionnaire evaluation results of the color schemes generated by system.
crossover rate and mutation rate respectively. Several experiments are needed to find the best values to adapt to each problem. The larger values of $k_1$ and $k_2$ imply larger crossover rate and mutation rate. As an exploratory study, this paper has only compared the performance of the proposed method with that of a general IGA. In future work, the proposed algorithm needs to be further optimized to improve the efficiency and quality of color matching.

(3) The participants in the experiment were students with a design background. Because industrial design students are familiar with product color matching, they could quickly establish the mapping relationship between color and image, thus accelerating the convergence of the algorithm. Further experiments should be carried out to simulate the color perception characteristics of real users.

8. Conclusion

Cultural and creative products should not only focus on functional design and styling design, but also on color matching. A good color matching can make the products bring different psychological feelings to people. Reasonable color design helps to convey brand image and shape products’ style and characteristics. To capture consumers’ perceptual demand for cultural attributes in the color matching design of cultural and creative products, this paper has described the application of an IGA, Kansei engineering, color harmony, and other aesthetic theories to color matching design.

A color database was constructed with 96 Chinese traditional colors and three non-colors as color samples. Using the semantic differential method, a color image preference experiment was conducted. Through factor analysis, six color image factors were extracted. Taking the color image factors as the optimization objective, a fitness evaluation function was constructed based on subjective image evaluation and objective visual aesthetics, and then the IGA was used to optimize the scheme group so that the color scheme satisfied user demands.

The advantages of subjective evaluation and objective calculation were combined in the evaluation process. Subjective evaluation is a good way to obtain users’ implicit psychological needs, but there is some uncertainty in subjective image evaluation. Therefore, gray theory was used to analyze the grayscale of subjective evaluation, and adaptive genetic operators were designed according to the grayscale of the fitness value to guide the evaluation process and improve the optimization efficiency, effectively alleviating human fatigue. According to the formal beauty rule of color, the harmony, balance, and symmetry were taken as indicators to measure the objective visual aesthetics in the color design of cultural and creative products. Finally, the color matching design of a speaker box was presented as an example to verify the design method. The results show that the color matching process of the proposed method is simple and provides a feasible way of improving color matching efficiency.

Declarations

Author contribution statement

Li Deng: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.
Fangyuan Zhou, Zhirui Zhang: Performed the experiments; Contributed reagents, materials, analysis tools or data.

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References

Birkhoff, G.D., 1933. Aesthetic Measure. Harvard University Press.
Cai, H., 2020. User Preference Adaptive Fitness of Interactive Genetic Algorithm Based Ceramic Disk Pattern Generation Method. IEEE Access.
Chen, P., Li, J., Pan, W., 2015. Product color design based on reuse of color scheme. Chin. J. Eng. Des. 22 (6), 546–551.
Gioaca, G., Napoleton, P., Schettini, R., 2019. Evaluation of Automatic Image Color Theme Extraction Methods. International Workshop on Computational Color Imaging.
Deng, J.L., 1982. The grey control system. J. Huazhong Univ. Sci. Technol. (Nat. Sci. Ed.) 10 (3), 9–18.
Deng, L., Deng, F., Wang, G., 2021. Application of artificial bee colony algorithm and back propagation neural network in color evaluation of human-machine interaction interfaces. Eng. Rep. 1–28.
Ding, M., Dong, W., Yang, C., 2013. Product color design based on multi-emotion. J. Mech. Sci. Technol. 27 (7), 2079–2084.
Dou, R., Zhang, Y., Nan, G., 2019. Application of combined Kano model and interactive genetic algorithm for product customization. J. Intel. Mannuf. 30, 2587–2602.
Dou, R., Zong, C., Nan, G., 2016. Multi-stage interactive genetic algorithm for collaborative product customization. Knowl. Base Syst. 92, 43–54.
Gong, D., Hao, G., Zhou, Y., Gao, Y., 2007. Theory and Applications of Interactive Genetic Algorithms. National Defense Industry Press.
Guo, F., Li, F., Nagamachi, M., Hu, M., Li, M., 2020. Research on color optimization of tricolor product considering color harmony and users' emotion. Color Res. Appl. 45 (1), 156–171.
Guo, G., Cai, J., 2008. Adaptive interactive genetic algorithms with grey for fitness of evolutionary individuals. Comput. Appl. 28 (10), 2525–2528.
Guo, G., He, L., 2009. Interactive genetic algorithm based on grey level for interval fitness. Comput. Eng. 35 (14), 232–235.
Guo, G., Wang, Y., 2011. Interactive Genetic Algorithms with Grey Level of Individuals Fitness. In: 2011 IEEE International Conference on Computer Science and Automation Engineering, Shanghai, China.
Guo, H., Li, J., 2020. Chinese Traditional Color – Color Aesthetics in the Forbidden City. Cicit Publishing Group.
He, J., Chen, D., Yu, S., 2020. Research on color design and evaluation method of cultural creative products based on color harmony theory. J. Northwest. Polytech. Univ. 38 (4), 766–773.
Hsiao, S.W., Hsu, C.F., Tang, K.W., 2013. A consultation and simulation system for product color planning based on interactive genetic algorithms. Color Res. Appl. 38 (5), 375–390.
Hsiao, S.W., Wang, M.F., Lee, D.J., Chen, C.W., 2015. A study on the application of an artificial neural algorithm in the color matching of Taiwanese cultural and creative commodities. Color Res. Appl. 40 (4), 341–351.
Hsiao, S., Yang, M., Lee, C., 2017. An aesthetic measurement method for matching colours in product design. Color Res. Appl. 42 (5), 664–683.
Jahanian, A., Vishwanathan, S.V.N., Allevbach, J.P., 2015. Autonomous color theme extraction from images using saliency. Proc. SPIE 9408, 940807.
Jia, Q., Zhang, L., 2014. Quick assessment of human-machine interface complexity in digital nuclear power plant based on image entropy. Atomic Energy Sci. Technol. 48 (12), 2370–2374.
Kapkin, E., Joines, S., 2018. An investigation into the relationship between product form and perceived meanings. Int. J. Ind. Eng. 67, 259–273.
Li, M., Xu, Q., Gao, D., Chen, B., Yuan, S., Xu, D., 2017. Color decision system based on hybrid intelligent method and multi-users' images. J. Computer-Aided Des. Comput. Graph. 29 (11), 2091–2099.
Liu, J., Liu, J., Liu, G., 2012. Color scheme design through color semantic and interactive genetic algorithm. J. Computer-Aided Des. Comput. Graph. 24 (5), 669–676.
Liu, S., Jiang, Y., Luo, H., 2018. Attention-aware color theme extraction for fabric images. Textil. Res. J. 88 (3), 552–565.

Table 10. Average scores of the color schemes of “fashion trend”.

| Color schemes | S1 | S2 | S3 | S4 | S5 |
|---------------|----|----|----|----|----|
| Average scores | 4.00 | 3.98 | 3.75 | 3.80 | 3.88 |
Liu, S., Luo, H., 2016. Hierarchical emotional color theme extraction. Color Res. Appl. 41 (3), 513–522.
Liu, X., Cao, Y., Zhao, L., 2016. Color networks of traditional cultural patterns and color design aiding technology. Comput. Integrated Manuf. Syst. 22 (4), 899–907.
Liu, X., Li, G., Sun, S., 2009. Color mapping design from image to 3D product model. J. Mech. Eng. 45 (10), 222–227.
Moon, P., Spencer, D.E., 1944. Geometric formulation of classical color harmony. J. Opt. Soc. Am. 34 (242), 46–59.
Nagamachi, M., 2002. Kansei engineering as a powerful consumer-oriented technology for product development. Appl. Ergon. 33 (3), 289–294.
Su, Y., Sun, H., 2019. Emotion-based color transfer of images using adjustable color combinations. Soft Comput. 23, 1007–1020.
Sun, J., Chen, A., Wang, S., 2007. Research on construction of color design system based on neural network and genetic algorithm. J. Eng. Des. 14 (3), 243–246.
Wang, M., 2018. A study on Fuzzy C-means application in Austronesian language cultural and creative product colors. Color Res. Appl. 43, 375–386.
Wang, T., Zhou, M., 2020. A method for product form design of integrating interactive genetic algorithm with the interval hesitation time and user satisfaction. Int. J. Ind. Ergon. 76, 102901.
Wang, X., Qin, J., Gao, Y., 2016. Artistic coloring: color transfer from painting. Int. J. Pattern Recogn. Artif. Intell. 30 (7), 1654005.
Wang, Y., Song, F., Liu, Y., Li, Y., 2021. Application of binary programming theory to product color planning with multiple constraints. Color Res. Appl. 46, 1091–1105.
Watkins, M.W., 2000. Monte Carlo PCA for Parallel Analysis (Computer Software). & Psych Associates, State College, PA.

Weingerl, P., Hladnik, A., Javorsiek, D., 2020. Development of a machine learning model for extracting image prominent colors. Color Res. Appl. 45, 409–426.
Xu, B., Liu, X., Lu, C., Hong, T., Zhu, Y., 2019. Transferring the color imagery from an image: a color network model for assisting color combination. Color Res. Appl. 44, 205–220.
Yang, L., 2013. A Study on the Use and Significance of Color in Classical Chinese Plays. Henan University, Kaifeng.
Yang, Y., Tian, X., 2019. Combining users’ cognition noise with interactive genetic algorithms and trapezoidal fuzzy numbers for product color design. Comput. Intell. Neurosci. 1–11.
Zhang, B., 2009. Research on Decorativeness of Chinese Traditional Mural Color. Soochow University, Suzhou.
Zhang, N., Yang, Y., 2019. Interactive product color design integrating users’ cognitive noise using interactive genetic algorithms. Mech. Sci. Technol. Aero. Eng. 38 (5), 698–703.
Zhao, L., Yang, L., Huang, X., 2018. Hierarchical multi-hive bee colony algorithm for computer aided color design. Comput. Integrated Manuf. Syst. 24 (2), 381–389.
Zhao, Z., 2014. China Traditional Clothing Dyeing Technique Inheritance and the Color Recovery. Qiqihaer University, Qiqhaer.
Zhu, X., Li, X., Chen, Y., Liu, J., Zhao, X., Wu, X., 2020a. Interactive genetic algorithm based on typical style for clothing customization. J. Eng. Fibers Fabr. 15, 1–9.
Zhu, Y., Xu, B., Liu, X., 2020b. Reference image aided color matching design based on interactive genetic algorithm. Packag. Eng. 41 (2), 181–188.