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Color Palette Generation of Mixed Color Images Using Autoencoder

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The color sensor, fundamental in designing image filter algorithms for smartphones, is often developed on the basis of the demands of commercial imaging applications. The creation of a color palette is an essential step for designers when planning color schemes. In this study, we introduce a method for generating blended color imagery, called the 'color image' in some previous works,[8,9] to construct personalized palettes that cater to individual emotional needs. We modified the training approach of the autoencoder, incorporating data related to emotions into the training samples. This allowed us to establish a correspondence between color imagery and palettes on the basis of Kobayashi's color image scale. Through linear interpolation calculations between different types of imagery, we derived the emotional coordinates of blended color imagery. Using these derived coordinates, we fed them into the trained autoencoder model to reconstruct the generated palette for blended color imagery. We conducted a visual evaluation experiment, and the results showed that the emotional conveyance of the generated blended color imagery palettes is consistent with human perception. Additionally, we presented two sample applications: emotional filters and background frameworks. We anticipate that the findings of this study can offer a new perspective for the development and application of the color sensor.

1. Introduction

The development of the color sensor as the foundation for the design of smartphone image filter algorithms is often guided by the demands of commercial image applications. The use of color in design has been extensively researched, and its effect on designers during the design process is higher than that of form.[1] Color is one of the important features in human visual perception, and many psychologists have studied the relationship between color and perception.[2] For example, Kaya and Epps found that color can affect cognitive performance.[3] Hanada used correspondence analysis to analyze the relationship between color and emotion,[4] whereas Chen *et al*. assigned colors on the basis of vocabulary and found many similarities in the responses of

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subjects from the UK and China.[5] Color is crucial in design, whether it is for website design, product packaging, or advertising posters, as it helps convey the designer's intended message and emotions. Generating the color palette is an important step in creating color schemes, and the right palette can significantly affect people's emotional responses. Traditionally, the correlation between color palettes and emotions is evaluated on the basis of the designer's experience. The automatic color palette generation method proposed in this study can help designers speed up the process of creating color schemes.

Color palette generation has gradually become an essential design tool in modern design, as demonstrated by the image-based color palette method developed.[6] This technique can not only be widely used in product design but also applied to various multimedia platforms, such as websites, applications, videos, and animations. With appropriate color palette generation technology, designers can more easily select the best color palette. Personalized color palettes are also gaining attention in multimedia design, as they can create an atmosphere that matches the emotional intent of the content and improve the user experience, as shown in Fig. 1. In recent years, personalized color palettes that reflect a person's emotions and personality have become increasingly popular, and studies have shown that people with strong personalities tend to prefer colors that represent their personality traits.[7] To meet this demand, we developed a method of generating a mixed color image to create personalized color palettes that match emotional needs. The proposed method involves creating a mixed color image with specific emotions and using an autoencoder to generate a color palette that reflects the emotional content of the mixed color image. As shown in Fig. 2, different degrees of color filters from sweet to bitter are generated. The generated color palette will be personalized and designed to elicit the desired emotional response. This method has the potential for revolutionary development in various industries.

Color plays a crucial role in design, and an appropriate color palette can affect people's emotional responses. We propose a method for generating a blended color image with personalized and effective qualities to create color palettes that meet emotional needs. The study uses the color image scale (CIS) research data,[8,9] which was created by Kobayashi through pioneering research on emotional vocabulary and color palettes using the semantic differential method and factor analysis, and shows the correlation between color and emotion on the CIS.

The first step was to reconstruct Kobayashi's CIS research into data that includes several color palettes for each color image and image location. In this study, we refer to image location as color image emotional coordinates (CIECs), where images and color palettes with adjacent CIEC locations are similar. Conversely, the farther the CIEC location, the greater the difference between the image and the color palette. Next, the data was placed into an autoencoder as training samples to train a spatial model similar to the original data for use in generating a blended color image. Finally, by linear interpolation, the blended CIEC was calculated and combined with the specified color palette in the trained model to generate a color palette for a blended color image.

Fig. 1. (Color online) Application of generated results on image filters.

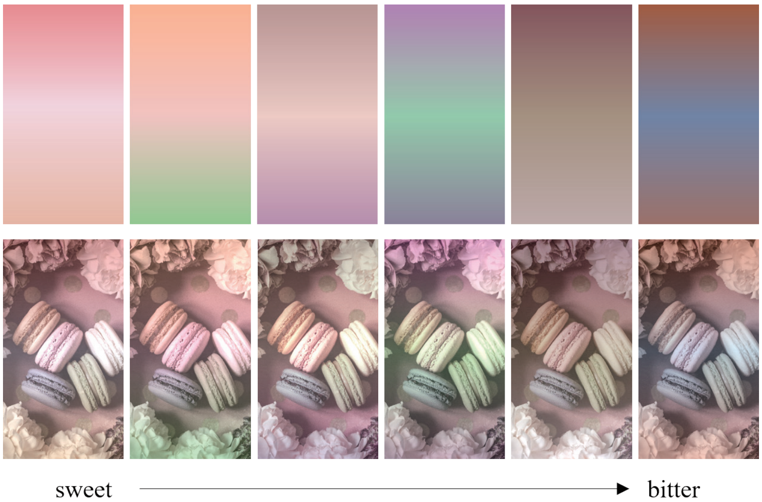


Fig. 2. (Color online) Results of generating color filters with varying degrees of sweetness to bitterness.

2. Data, Materials, and Methods

2.1 Color palette generation

One common way to generate a color palette is by extracting colors from an image, such as using image segmentation in the HSI color space to produce a layered color palette.(10) Wang *et al*. mapped the relationship between color themes and affective words to Kobayashi's CIS, and then expanded the data using internet resources to convert the emotional representation of images using this database.(11) Another method is to extract the emotional value of a theme from pixels.(12) Kim and Suk proposed a method of generating emotionally diverse key colors using techniques such as neural networks and emotion analysis, which can generate emotionally appropriate colors on the basis of user needs.(13) Kita *et al.* proposed a color-palette-based image search method that uses color weight and color palette matching to search for relevant images based on user-specified color palettes, further expanding the application range of color palettes.(14) Xu *et al.* aimed to explore the connection between words and colors, which may vary across different cultural backgrounds.(15) To achieve this, researchers used the CIS tool and crawled a large number of image data from sites such as Flickr and Google Image Search to build a dataset containing different word and color associations. This data set was used to train the model to evaluate the degree of association between different words and colors.

These studies demonstrate the diversity and importance of generating color palettes. Whether generating a color palette from keywords or images, the ultimate goal is to allow colors to convey the emotions that viewers may perceive, further affecting human perception.

2.2 Color image

The combination of colors in images can connect users on an emotional level, making it an important tool in the field of design. According to Zhang and Yang,(16) color is a psychological attribute that evokes emotions in visual experiences and creates emotional resonance with people. Kobayashi's CIS is a dataset that is relevant to this. Kobayashi first positioned 140 monochromatic colors on a two-dimensional CIS, and then used psychological experiments to position adjectives describing a color image on a similar scale, known as the adjective image scale.(8) On the basis of monochromatic colors, a series of color combinations applicable to design were then developed, and in 1991,(9) the keyword image scale and the color combination image scale were used to record more detailed data on color combinations. These color combinations are represented by the Munsell notation,(8) and we obtained the required sRGB data by interpolating the renotation data (xyY values) provided by the Munsell Color Lab. (17) The 174 representative color images from the research were positioned on a scale ranging from −3 to 3. The horizontal axis (x-axis) scale of −3 to 3 represents warm–cool variations, whereas the vertical axis (y-axis) scale of −3 to 3 represents hard–soft variations. We obtained the required raw data for this study by manually measuring the central coordinates of color imagery texts, as per original data in the aforementioned book (pp. 12 and 13).

2.3 Autoencoder

The autoencoder (AE) and generative adversarial networks (GANs) are the commonly used generative models in deep learning. AE is typically used for the dimensionality reduction of input data and for reconstructing high-dimensional data. It consists of an encoder and a decoder, where the encoder encodes the high-dimensional input data into a low-dimensional representation and the decoder decodes the low-dimensional representation back into high-dimensional output data. During this process, the model learns the mapping between the input and the output, reducing the error between the input and the decoded data. Common applications of AE include image, speech, and text generation. For example, Li *et al.* proposed a method for image classification using AE in the YCbCr color space to reduce computational complexity.(18) Hashisho *et al.* used a denoising AE with U-Net architecture for the color restoration of underwater images,[19] whereas Gomes *et al.* used AE for correcting images under different lighting conditions.[20]

GANs are models composed of two neural networks: a generator and a discriminator. The generator attempts to generate data that is similar to real data, whereas the discriminator attempts to distinguish between real data and data generated by the generator. These two networks compete with each other until the generated data is indistinguishable from the real data. GANs are commonly used for image generation, image style transfer, automatic coloring, and data augmentation, among other related techniques. For instance, Chen *et al.*[21] proposed the Cartoon GAN model combined with the VGG network, which converts real photos into cartoon-style images.

AE models are mostly used for image color reconstruction. We utilize the characteristics of AE and apply them to color generation. Instead of using traditional input data, sRGB values and emotional coordinates are used as input, with the goal of reconstructing data that is similar to the original data. By changing the emotional coordinates in the input data, a related color palette can be obtained.

2.4 Methods

The method for creating a mixed color image palette involves first digitizing Kobayashi's CIS data. Next, AE is trained on the CIS data to reconstruct its features. Finally, the mixed CIEC and specified color palette are fed into the trained model for generation, resulting in a mixed color image palette. The next section will showcase the generated results. Kobayashi's CIS is a scale that links image and color together, with data including CIECs and color palettes. This configuration is helpful for systematically implementing color schemes. In this study, the original data of CIECs and color palettes were digitized and AE was used to reconstruct CIS as shown in Fig. 3, obtaining data that is similar to the original data to facilitate subsequent generation.

We modified the typical training method for AE by incorporating the color palette of CIS and its corresponding CIECs into the training samples. The training samples were sourced from a total of 174 color images, comprising 1132 color palettes, allowing us to establish the data relationship between color images and their respective palettes, as illustrated in Fig. 4. During training, we employed a seven-layer MLP model (11-256-256-3-256-256-11), with the three middle cells representing the latent variables. The input and output layers each received 11 values, including the color frequencies of three sRGB colors for color imagery and its corresponding x, y values. In this study, we utilized the Adam optimizer, without the use of dropout layers, and training concluded after 500000 epochs. Here, $\boldsymbol{c}$ represents the color palette for each color image in the original data and (x, y) denotes the CIEC for each color image. After dimensionality reduction by the encoder and dimensionality restoration by the decoder, we obtained the reconstructed color palettes $\boldsymbol{c'}$ and (x', y'). After completing AE training, during the generation of mixed imagery color palettes, it is possible to specify any two-color images. The CIECs for different degrees of imagery variation can be obtained through linear interpolation based on their respective CIECs. The number of interpolation points, N, can be set

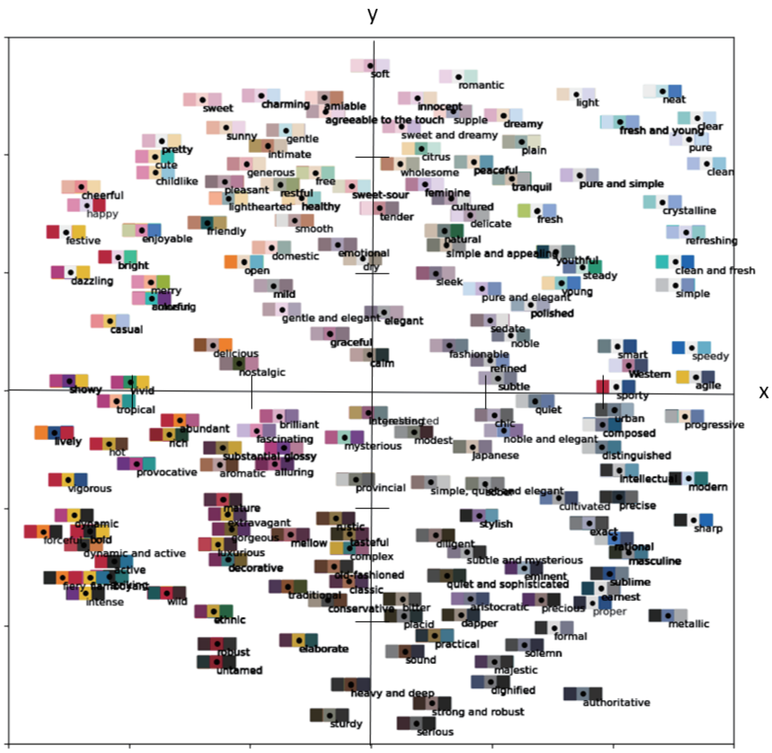


Fig. 3. (Color online) Reconstructed CIS.

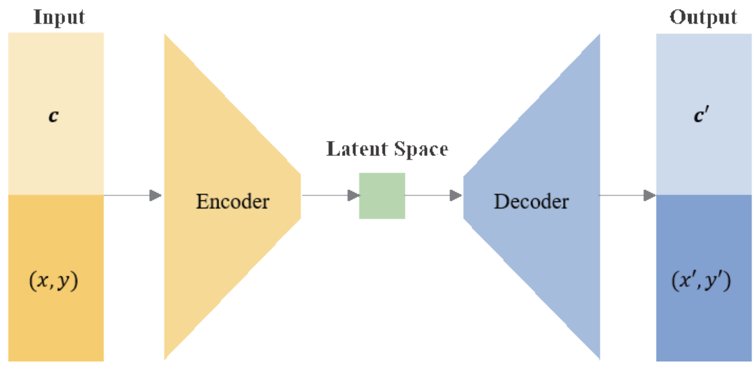


Fig. 4. (Color online) Autoencoder.

as needed. The CIEC values at these interpolation points can be used to generate the desired mixed imagery color palettes.

In this study, we incorporated a specified color palette of a color image (e.g., sweet) and the CIEC of another color image (e.g., bitter) outside the specified color image into the system architecture of AE. The results obtained through the linear interpolation of the CIEC were fed into the trained AE model. The formulas are as follows:

$$x = x_1 t + x_2 (1 - t) \tag{1}$$

and

$$y = y_1 t + y_2 (1 - t), \tag{2}$$

with $t = i / N$, where N is the number of desired generated samples. (x_1, y_1) represents the CIEC of the specified color scheme sweet and (x_2, y_2) represents the CIEC of another specified color scheme bitter. Figure 5 illustrates the process of generating a mixed emotional color scheme from the sweet color scheme and sweet's emotional coordinates to bitter's generated color scheme. This generation method allows for mixing two or more color schemes with mixed emotional color schemes.

Figure 6 shows the results of five generative color palettes by linear interpolation using the sweet–bitter and colorful–simple and appealing CIECs, along with the corresponding color schemes generated by combining them with the sweet and colorful color palettes, respectively.

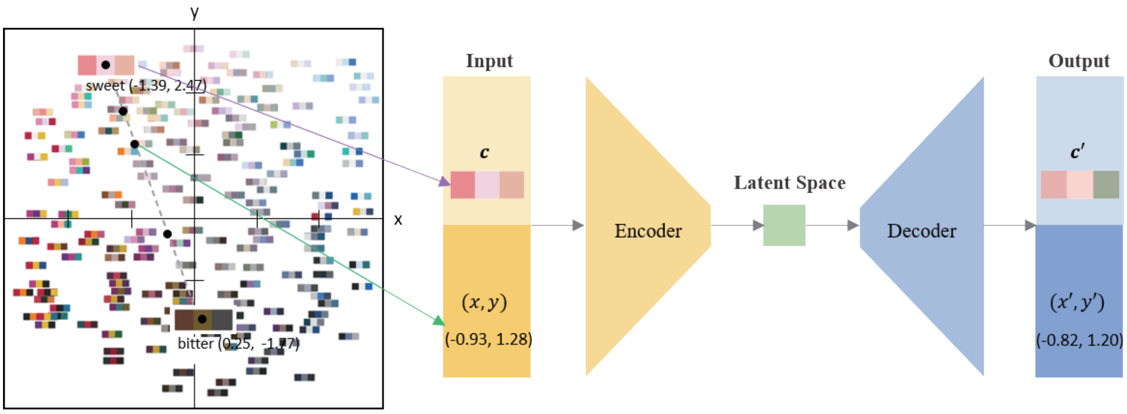


Fig. 5. (Color online) Generating a color palette of mixed color images.

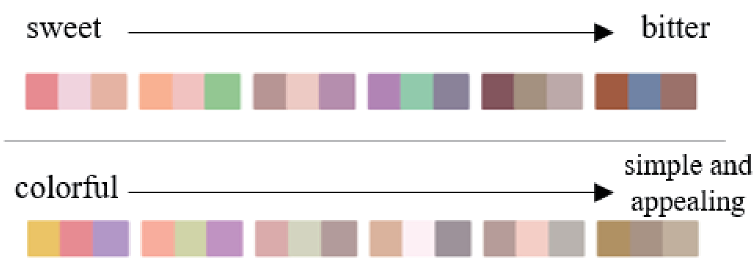


Fig. 6. (Color online) Generating results of mixed color images.

3. Results and Discussion

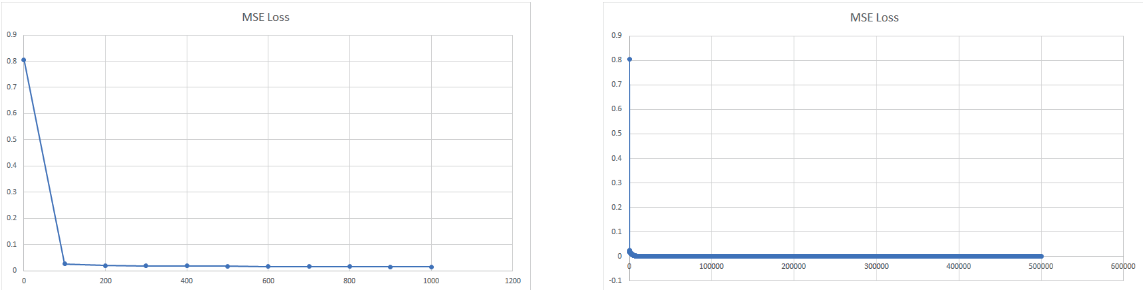
In this section, we will explain the AE training samples, the AE training process, and the results of the color palette generation method that we proposed. We will also assess the results generated through visual experiments and provide some potential applications for this method.

Firstly, the AE model, as mentioned earlier, is a traditional neural network architecture composed of multiple dense layers. The training data consisted of 1132 samples of CIS color combinations, originating from 174 different color images. Note that the number of color combinations per color image is not uniform. Each color image is associated with a single independent x-y coordinate pair, representing the emotional tendencies of cool–warm and soft–hard. These color values and the CIEC *x*-*y* raw data are sourced from the original CIS book (as referenced). However, as the original data did not provide corresponding sRGB color values, the values used in this research experiment were obtained through interpolation using the Munsell notation provided in Kobayashi's earlier research (as referenced). Additionally, the x-y data was manually measured.

The training of AE employed the MSE loss function and utilized the Adam optimizer for estimating all weight parameters. The training process was highly stable and rapidly converged. By epoch=1000, the MSE had already decreased from 0.805848 to 0.014947 and continued to steadily decrease. To achieve the goal of generating colors with almost imperceptible differences, the training was carried out until epoch = 500000, ultimately reducing the MSE to 0.00000560, nearly approaching zero. Figure 7 illustrates the convergence of AE training, with Fig. 7(a) representing the stages from epoch = 1 to epoch = 1000, and Fig. 7(b) depicting the entire process from epoch = 1 to epoch = 500000.

Subsequently, we conducted a series of visual observation assessment experiments. We selected 10 pairs of color imagery categories, namely, sweet–bitter, colorful–simple and appealing, old-fashioned–modern, casual–formal, showy–pure and simple, soft–sharp, happy–solemn, wild–urban, sweet and dreamy–practical, and mature–youthful. For each pair, 25 color palettes were generated (N = 25), resulting in a total of 10 color palettes. These color palettes were distributed to 60 participants in the form of an online questionnaire. Participants were asked to provide their observations and perceptions regarding the degree of imagery blending in the generated color palettes. An example of the questionnaire is shown in Fig. 8. We set the order of color palettes generated by AE as the standard answer and arbitrarily selected three color palettes, asking participants to restate the order they perceived. Finally, we assessed whether the participants' answers matched the order generated by AE, and the results are presented in Table 1. The findings indicate a positive recognition of the visual conveyance of the generated color palettes. The imagery presentation of our generated color palettes exhibited consistency in the emotional blending degree order with the perception of the majority of humans in most of the tests.

In terms of application, in this study, we incorporate the generated mixed color image palette results into design templates to create photo filters or frames, as shown in Fig. 9. Figures 10 and 11 respectively show the results of applying design templates as filter effects to photos and their



(a) (b)

Fig. 7. (Color online) Convergence process of AE training: (a) before 1000 epochs and (b) entire process.

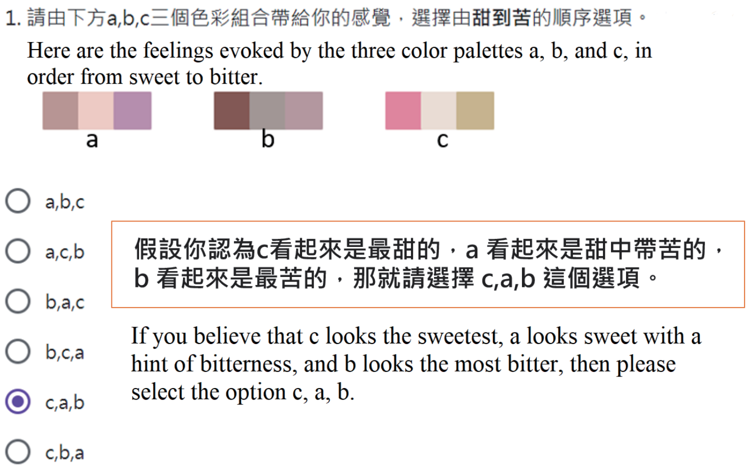


Fig. 8. (Color online) Sample questionnaire image.

Table 1
Results of visual observation assessment experiment.

	Color image 1	Color image 2	Response consistency
1	sweet	bitter	0.89
2	colorful	simple and appealing	0.89
3	old-fashioned	modern	0.75
4	casual	formal	0.22
5	showy	pure and simple	0.67
6	soft	sharp	0.60
7	happy	solemn	0.91
8	wild	urban	0.52
9	sweet and dreamy	practical	0.57
10	mature	youthful	0.49

use as frames. With the prevalence of social media today, users commonly express their moods through photos. Designing filters or frames allows for more variations in photos and enhances the conveyance of emotions.

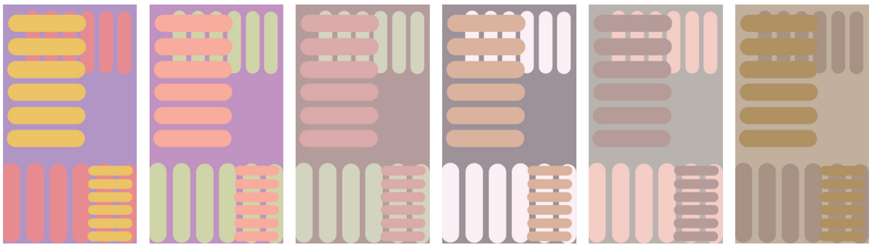


Fig. 9. (Color online) Design templates of various color palette layouts for the colorful to simple generated results.

Fig. 10. (Color online) Results of adding design frames to photos.

Fig. 11. (Color online) Results of applying filters to photos.

4. Conclusion

The image color filter method we designed offers a potential avenue for the development of color sensor technology. In this study, we utilized AE to generate color palettes of a mixed color image, with the aim of assisting designers in personalizing their color schemes. We used data from CIS and transformed it into numerical data, which was then fed into AE as training data to construct a data mapping relationship between a color image and color palettes. Finally, the emotion coordinates of the specified mixed color image and color palettes were fed into the trained AE model to generate customized palettes with a different mixed color image. As a result, the application in conveying emotions in photographs allows users to express stronger feelings through color palettes that contain a different image. The effectiveness of this approach can be observed from the sample image mentioned above, highlighting the necessity of research in developing color emotional filters for photos.

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