Automatic Image Style Transfer Using Emotion-Palette<br>Jing Huang ${ }^{a b}$, Shizhe Zhou* ${ }^{a b}$, Xianyi Zhu ${ }^{a}$, Yiwen $\mathrm{Li}^{a}$, Chengfeng Zhou ${ }^{a b}$<br>${ }^{a}$ College of Computer Science and Electronic Engineering, Hunan University, Changsha 410082, China<br>${ }^{b}$ Key Laboratory of High Performance Computing and Stochastic Information Processing, Ministry of Education of China, China


#### Abstract

Palette-based color editing can form an intuitive interface through which novices can perform interesting color modifications. However, because such modifications involve pixel-level operations, considerable labor is needed to accomplish an image's emotion transformation. In this paper, we propose a novel color-transferring framework for image based on palettes to evoke different emotions. The purpose is to use the emotion-related color combinations to change the picture's original color palette to obtain stylized images. For an input image, the optimized k-medoids algorithm is used to create a set of the most representative color palettes. The system search for the best color combinations from a predefined database according to the color palette characteristics of the input image. Finally, using the selected emotion-palette we conduct a color transfer. The novel method can transfer a wide range of image into a new color style depicting the required emotional impact.


Keywords: color combinations, emotion-palette, color transfer

## 1. INTRODUCTION

Color is an indispensable part of the visual world, and color is a primary feature when conveying a particular mood in art, painting and visualization. By modifying the color of an image, a user can evoke different emotional styles in the picture and enhance its beauty. Therefore, researchers are increasingly interested in extracting the emotional color of the image and then using different methods to recolor the image. Reinhard et al. ${ }^{[1]}$ first proposed a color transfer algorithm using a reference image.Yang and Peng ${ }^{[2]}$ proposed a color-transferring algorithm that considered the relationship between perceived color and the emotion induced.
After Yang and Peng's innovative work, color emotion has been applied from many aspects. Csurka et al. ${ }^{[3]}$ learned the moods and emotions evoked by color combinations. Liu et al. ${ }^{[4]}$ demonstrated a method that can transfer a wide range of styles from image collections to users' photos. However, when using color emotions for a variety of research, some problems will occur. First, emotions can be expressed by a single color, three color combinations, or multiple-color combinations, and there is no obvious criterion for associating color and emotion. Second, a style transfer method similar to Liu et al. ${ }^{[4]}$ requires one or multiple reference pictures, and the user may not have enough aesthetic knowledge to select appropriate reference images. Finally, it is important to provide an emotion-based recommendation system for users' pictures.

To solve these problems, in this paper, we propose a novel color-transfer framework based on photo palettes and emotional color combinations. This framework make it much easier for users to stylize photos. Unlike traditional singlecolor and three-color combinations databases, this paper use five-color combinations to measure color emotions, which more delicately reflects the emotional content of the picture. Then, because our framework does not need to provide reference pictures, it directly selects an emotional color combination from the database. Finally, system both provides numerous emotional styles and recommends appropriate emotions for the image. We use the $k$-medoids clustering algorithm to determine the five main colors in the input image, k -medoids is similar to the k -means algorithm but is more resistant to noise. Figure 1 shows the best styling results recommended by the system for the picture.

Our work has three main contributions. First, we introduce a convenient, interactive user interface that novices can use to select a color palette to recolor an image. Second, we create a novel database of emotion-palettes based on the colors designed by amateur designers containing colors that are richer than the standard database compiled by skilled designers. Finally, our system can search this database to automatically select the best emotion-palette to match the picture, giving the image a new emotional style.

The rest of this paper is organized as follows. Section 2 reviews previous work in related areas. Section 3 describes the database we created and used for the experiment. In Section 4, the emotion-palette for the whole process of photo

## *Corresponding author : shizhe@hnu.edu.cn(Shizhe Zhou).

stylization and an accelerated method are introduced. Section 5 provides comparisons with other methods and evaluations. Section 6 shows the results of several image editing applications that applied our approach. Finally, Section 7 conclude the paper and discuss future work.


Figure 1. Image style transfer. From left: original; Examples of user stylizing a photo using the emotion-palette recommended by the system: Sensual, Spiritual, Serene.

Video 1. The video of image style transfer:https://m.weibo.cn/5579577425/4185962437115337

## 2. RELASTED WORK

### 2.1 Color transfer

The existing color-transfer methods can be divided into two categories: histogram-based and clustering. The histogrambased approach matches the histograms of the source image and the target image to transfer colors between them. The clustering method extracts a few of the most representative colors from the image as an abstraction of the color distribution in the image.
The first color transfer method was proposed by Reinhard et al. ${ }^{[1]}$. It matches the mean and standard deviation of a reference image based on the pixel histogram of the input image. Pitie et al. ${ }^{[5]}$ gradually matched two 3D color histograms by matching 1D marginal distributions. Chang et al. ${ }^{[6]}$ classify pixels into basic color categories and then match input pixels to reference pixels in the same category. Yoo et al. ${ }^{[7]}$ exploited their main colors to find local regions between the two images corresponding to statistical shifts. Note that all these methods require a reference image as an input image.

The second color transfer method uses a clustering algorithm such as k-means, k-medoids, mean-shift algorithm and the expectation maximization (EM) algorithm for color clustering. The k-means clustering algorithm ${ }^{[8]}$ extracts the main color of the picture using a limited number of iterations. Unfortunately, k-means clustering is known to be sensitive to outliers. Therefore, we sometimes use k-medoids ${ }^{[9]}$, which represent objects called medoids rather than centroids. It is less sensitive to outliers than is k-means clustering. Cheng ${ }^{[10]}$ first modified the mean-shift algorithm and used it for non-parametric clustering. Then, Comaniciu and Meer ${ }^{[11]}$ applied the mean-shift algorithm to image filtering and segmentation. The EM algorithm ${ }^{[12]}$ can control spatial and color smoothness to infer the natural connections between pixels. For this study, we chose the k-medoids clustering algorithm.

### 2.2 Palette based recoloring

Image recoloring algorithms can be divided into three categories: example-based ${ }^{[13]}$, stroke-based , and palette-based ${ }^{[14]}$ methods. In this paper, we use the palette-based recoloring method for color transfer. The color theme of an image is a small group of colors, usually 3 to 7 that best represents the image. Lin and Hanrahan ${ }^{[14]}$ proposed a method for coloring vector art by palettes based on a probabilistic model. Chang et al. ${ }^{[15]}$ introduced an interactive GUI interface that allows a user to recolor an image by editing the palette; this approach achieved good recoloring results. Recently, Zhang et al. ${ }^{[16]}$ proposed a color decomposition optimization method that decomposes the colors. Users can then use the modified palette to recolor the image. Zhang et al. ${ }^{[17]}$ provided a data-driven palette for real-time display of updated colorization results.

### 2.3 Color emotions

Color is an important factor in inducing human emotions. The sensations caused by a single color or by color combinations are called "color emotions". A single color has its own characteristics. Ou et al. ${ }^{[19]}$ classified single-color emotions and developed a color emotion model based on color science. Several studies ${ }^{[18,19]}$ have shown that color combinations can evoke emotions. Kobayashi ${ }^{[20]}$ developed a color image ratio that matches the color combinations and the corresponding emotional words. Csurka et al. ${ }^{[3]}$ solves the problem of associating combinations of colors to abstract
categories by using combinations of colors or color palettes. Wang et al. ${ }^{[21]}$ presented a data-driven method to enhance a desired color theme in an image that can quantify the differences between an image and various color themes. Liu et al. ${ }^{[4]}$ demonstrated a data-driven system that automatically transfers a style to a user's photos. Because emotions are complex and changeable, a single-color emotion cannot meet the needs of users. Instead, color combinations are more suitable for describing the emotional color of an image.

## 3. CONSTRUCTING COLOR COMBINATION DATABASE

Two categories of emotional databases are widely utilized by researchers. The first category is generated by psychologists and graphic design experts in the field of color combinations. The second comes from an amateur designer's own creations, who put their color combinations into a database on the Internet available to other users. The former has only a few examples of color combinations per class, while the latter's color combinations are richer, but the color ratios may be improper.

### 3.1 Database selection

Kobayashi ${ }^{[22]}$ created a database consisting of 900 three-color combinations corresponding to 180 emotional words. The Pantone color scheme ${ }^{[23]}$ contains 27 emotional words, where each word is associated with 24 three color combinations. These two databases are professional-level databases. Csurka et al. ${ }^{[3]}$ first used an online emotional database created by graphic design enthusiasts, in which emotions are loosely marked by users with natural language words.
We reduced the 27 emotional words in the Pantone color scheme ${ }^{[23]}$ to 24 words, downloaded approximately 12,000 palettes from the graphic design enthusiast's popular social network ${ }^{[24]}$ using the 24 key words, and selected 576 fivecolor palettes according to Kobayashi's three-color palettes ${ }^{[22]}$. Therefore, our database contains 24 schemes, and each scheme contains 24 five-color palettes. The 24 emotional words are Serene, Earthy, Mellow, Muted, Capricious, Spiritual, Romantic, Sensual, Powerful, Elegant, Robust, Delicate, Playful, Energetic, Traditional, Classic, Festive, Fanciful, Cool, Warm, Luscious \& Sweet, Spicy \& Tangy, Unique and Naturals. Figure 2 shows four sets of "Cool" color combinations.


Figure 2. Based on Kobayashi's original three-color palettes,the database produced five-color palettes according to a color coordination ratio. There are 4 color palettes for "Cool".

### 3.2 Database optimization

The database is composed of five-color combinations. That is, each palette has five colors. After cycling through five colors in every possible combination using a permutation methods, then choose the most appropriate combination. In this paper,Lab is used as the reference color space, using the monotonic luminance L of the original palette to select a combination that is consistent with the monotonicity of the original palette from the all combinations. This database optimization method makes the luminance consistent between the stylized picture and the original picture. Figure 3 shows the improvement of the recolor effects using a palette based on the L channel.

(a) Input image

(b)

(c) "Powerful"

Figure 3. Steps in transferring colors to the "Powerful" scheme. (a)The original palette of the input image; (b) transfer to a palette in the original database; (c) transfer to the optimized palette.

## 4. IMAGE STYLE TRANSFER

This section describes a simple process to complete image style transfer based on an emotion palette. This process is divided into four steps. Figure 4 shows the process overview of the image style transfer. First, use the k-medoids cluster to generate a palette of the picture. Second, according to the picture characteristics, select the most representative color combination for each emotion from the 24-emotion database. Then, select the emotion that best matches the picture from the emotional schemes. Finally, use the color transfer method to recolor the image. The system also provides an accelerated module that improves the color transfer speed.


Figure 4. Process overview of the image style transfer according to the selected palette, which generates different picture styles.

### 4.1 Palette generation using clustering

Clustering methods have been compared and studied in different works ${ }^{[25,26,27]}$. Contrasted with previous works ${ }^{[26,15]}$ which adopted the EM algorithm and k-means algorithm, this paper utilize the k-medoids algorithm ${ }^{[9]}$ for clustering. For discrete data such as pixels, k-medoids shows better results than does k-means.

The default value of k is 5 in the paper. It is estimated that $\mathrm{k}=5$ provides a good experience. However, when the k medoids algorithm is used directly to cluster the image pixels, for a large image, the calculation for each iteration will be time consuming. Therefore, this paper use a fast k-medoids image clustering algorithm ${ }^{[9,15]}$. The algorithm preprocesses all the pixels of the image and reduces the number of clustering points to $16 \times 16 \times 16=4096$. The k-medoids algorithm completes the data object clustering through iterations of the center point and minimizes the differences between classes, Then repeat the above center selection process until k centers have been selected.After analysis, the k-medoids algorithm can select the five color combinations with the largest distances from each other.

### 4.2 Defining the color combinations of emotions

There are 24 emotion categories in our database. Each emotion contains 24 candidate color combinations in which only the specific color combinations represent the corresponding emotion. To determine which combination is most suitable for a certain emotion, the candidate color combination that presents the minimum Euclidean distance from the generated palette in the previous step is appropriate. This selection procedure is formulated as follows.

The definition of an emotion is related to the distance between colors. We define the distance between two themes as the minimum distance from one color to another and use Euclidean distance to classify the emotions:

$$
\begin{equation*}
\min _{i}\left(\sum_{j=1}^{5} \sum_{k=1}^{3}\left\|C_{O}^{k}-C_{P}^{k}\right\|_{2}^{2}\right) \tag{1}
\end{equation*}
$$

where $i=1,2, \cdots, 24$ is the $i^{t h}$ scheme of the 24 schemes and $j=1,2,3,4,5$ is the $j^{\text {th }}$ color in the five-color combinations.The $k=1,2,3$ are the RGB values of the $j^{t h}$ color, $\mathrm{C}_{O}^{k}, k=1,2,3$ are the RGB values of the colors in the input image palette, and $\mathrm{C}_{p}^{k}, k=1,2,3$ are the RGB values of the colors in the database palette.

### 4.3 Emotion-palette selection

The image style transfer need to search for the emotions that best match the picture among all the emotions and use those emotions as the emotions of the picture. We compare each representative color combination of the emotion and the picture palette combinations and select the color combination closest to the original palette. To do this, the system need to calculate the similarity between the representative color combination of the emotion and the original color palette of the picture. To find the selected color combination closest to the original picture palette, we introduce a coefficient for the picture palette $C_{i}$ :

$$
\begin{equation*}
\lambda_{i}=\frac{N\left(c_{i}\right)}{N(\text { input })}, d_{j}=\left|P_{C_{i}}^{j}-P_{(x, y)}^{j}\right| \tag{2}
\end{equation*}
$$

where $j=1,2,3$ are the values of L , a , and b (in Lab space) of the color, respectively. $P_{C i}^{j}$ represents the Lab color values of the $i^{\text {th }}$ palette, $P_{(x, y)}^{j}$ is the Lab color values of the input image at pixel (x,y), $d_{j}$ is the distance between the Lab color values of the $i^{\text {th }}$ palette and the input image at pixel ( $\mathrm{x}, \mathrm{y}$ ), and $N\left(C_{i}\right)$ is the number of pixels when $d_{j}<=10$. $N$ (input) represents the number of pixels in the picture. Figure 5 shows that this coefficient is the proportion of each color in the palette.


Figure 5. The ratio chart of the five colors of the palette in the image
To select the closest color combination to the picture palette, the paper use the following formula:

$$
\begin{equation*}
\min _{j} \mathrm{D}(j)=\sum_{i=1}^{5} \lambda_{i}\left(\left|R_{D_{j}}^{i}-R_{C}^{i}\right|^{2}+\left|G_{D_{j}}^{i}-G_{C}^{i}\right|^{2}+\left|B_{D_{j}}^{i}-B_{C}^{i}\right|^{2}\right) \tag{3}
\end{equation*}
$$

where $j=1,2, \ldots, 24$ represents the 24 emotion schemes, ( $R_{D_{j}}^{i}, \mathrm{G}_{D_{j}}^{i}, B_{D_{j}}^{i}$ ) are the RGB values of the $i^{\text {th }}$ color of the five-color combination in the $j^{\text {th }}$ scheme, and ( $R_{C}^{i}, G_{C}^{i}, B_{C}^{i}$ ) are the RGB values of the $i^{\text {th }}$ color of the palette in the input image. Our system will recommend the minimum $\mathrm{D}(\mathrm{j})$ value of the representative color combination of each emotion to the user, who can then apply the selected emotional color combination to stylize the image.

### 4.4 Image color transfer

In this section, it introduces the use of emotional palettes selected from the database. Specifically, it focus on image color transfer based on the emotion-palette. this paper use the color transfer algorithm proposed by Chang et al. ${ }^{\text {[15] }}$ where there is no need to select the desired target image.Stylizing images by manipulating color palettes is a challenging task in image editing. Now that we have a set of palette colors, we must change the five main colors to change the style of the picture. Maintaining compatibility and coordination between the five colors is very important, because stylized images must avoid the color bleeding or color incongruity phenomena. The novel color transfer method can achieve a
result with good color balance. Figure 6 shows the process of style transfer. The five pictures generated in the process also maintain color balance.


Figure 6. The process of style transfer. First, extract the color palette of the image, and then, according to the selected color palette in the database to edit the palette. Finally, generate a stylized image with "Spiritual" scheme.

### 4.5 Acceleration

Because the proposed color transfer equation requires RBF interpolation to solve the multi-palette weight $W_{i}(x)$, it is computationally expensive to perform matrix calculations on images. Here, this paper introduce an acceleration scheme that enables more efficient and scalable color transfer on images. In principle, RBF calculations need to be performed only after the initial palette is created. We further accelerate the computation by caching these weights $W_{i}$ at a uniformly sampled $g \times g \times g$ grid of locations in the RGB cube. Next, during color editing, when the $C_{i}^{\prime}$ are known, the system can use the precomputed weights to calculate the output color $f(x)$ at these g3 positions. Finally, to recolor each pixel in the image, trilinear interpolation is used on the eight nearest grid values.
In general, in most cases, our approach completes the image styling process in the least amount of time. Table 1 shows the time consumption required by each method to complete the picture styling. These experiments were executed on a desktop computer with a 4.2 GHz Intel Core 2 i7-7700k CPU.

Table 1. An Acceleration.

| Image size | $100 \times 100$ | $300 \times 300$ | $500 \times 500$ |
| :--- | :--- | :--- | :--- |
| EM | 21.5 | 64.04 | 394.3 |
| Without acceleration | 6.12 | 32.4 | 60.6 |
| Acceleration | 1.38 | 11.64 | 26.62 |

## 5. EVALUATION

In this section, it is important to evaluate our approach from three aspects. The first is to compare the method and other color transfer methods based on five-color combinations, three-color combinations and a single color. The second is to evaluate user satisfaction through a user study. This is followed by comparing to the results of other style transfer methods.

### 5.1 Comparison with other color-combination methods

There is a big difference in style transfer methods that use single colors and those that use color combinations. Figure 7 shows the results of style transfer using a single color, three-color combinations and five-color combinations. It is show that style transfer using a single color is implemented by moving the means of the Lab color values of the input images and that it is similar to the results of using the three-color combination proposed by Li et al. ${ }^{[26]}$. This paper use the five color combinations recommended by the system to change the color of the original picture so that the picture visibly presents a new color.
Compared to the transfer results using single colors and three-color combinations, the five-color combination results have three advantages. First, using five-color combinations to represent emotions causes the color transfers in an image
to be conducted separately in different image regions, resulting in more colorful and emotionally rich images. Second, using five-color combinations avoids situations in which some of the picture colors are too bright. Finally, by using five-color combinations as a whole to change the picture colors, the results will be more natural.


Figure 7. Comparison of style transfers using single colors, three-color combinations and five-color combinations. The original image is on the left, and the columns from left to right show the original image transferred to four different schemes. From top to bottom, the rows show the style transferred using single color, the three-color combinations introduced by Li et al. ${ }^{[26]}$, our results using three-color combinations and our results using five-color combinations.

### 5.2 User study

Evaluating tasks using personal preferences is challenging. In this study, 4 photos are transferred to 4 color themes recommended by our system and to two randomly selected color themes using our proposed approach. Each user is asked to rate these six emotions. For example, in Figure 8(a), the system recommended emotions are: Playful, Robust, Spiritual, and Traditional, while the randomly selected emotions are Powerful and Cool.The user's own feelings are used to determine which emotional color is felicitous. A total of 30 users participated in the study. Each user evaluated 30 images. In total, 180 color themes were evaluated.We analyzed the evaluation results of the four pictures in the survey.



Figure 8. User study - user's satisfaction of four emotion recommended by our system for the four picture. From left: input image, the four stylized images by using the emotions recommended by our system, two stylized images based on randomly selected emotions.

As shown in Figure 8, the result achieve an average user satisfaction rate of $80 \%$ with an emotion recommended by our system. We can improve these results in the future by better describing each emotion.

### 5.3 The results of other style transfer

In this experiment, it demonstrated that our method can achieve good style transfer results. Figure 9 shows a comparison of our approach with other methods. From left to right are the results of Wang et al. ${ }^{[21]}$, Liu et al. ${ }^{[4]}$, Pitie et al. ${ }^{[5]}$ and Csurka et al. ${ }^{[3]}$. From top to bottom are the original photos, their results, our results using their palette, and our final result. The third row demonstrates that we can use their palettes to achieve the same effect as their method, while the fourth row is the result of the image style transfer produced by using our own palette based on the input image. our approach takes advantage of the color themes provided by our database, saving user the effort of finding suitable references. Our results have a more natural looking appearance.


Figure 9. Comparison to the style transfer results. Top to bottom: original photo, their result, our results by their palette, our final result. Left to right: the results of Wang et al. ${ }^{[21]}$, Liu et al. ${ }^{[4]}$, Pitie et al. ${ }^{[5]}$ and Csurka et al. ${ }^{[3]}$. There are four emotion schemes, such as: Energetic, Traditional, Capricious, Sensual.

## 6. APPLICATIONS

Here, it is show a variety of applications based on palette to demonstrate the extensibility of our approach.

### 6.1 Color transfer

The method of this paper can not only change the colors of the picture using a color palette from the database but also recolor a picture from a given reference image.


Input


Luan at al.


Reference


Our result

Figure 10. Color transfer. Our method can only transfer colors between the two image, and Luan et al. ${ }^{[28]}$ change the property of the bottle and turn the transparent bottle into an opaque bottle.

The method can assign the palette colors of the reference image to the target image; then, the color and tone are transferred to the target image. Compared with the method of Luan et al. ${ }^{[28]}$, which introduces a deep learning method for transferring the style between images, our color transfer is more flexible because it can choose any color from the picture to recolor the target image. Figure 10 shows that our method can match a transparent perfume bottle to a fireball and maintain the original transparent property of the bottle.

### 6.2 Image classification

The system can exist in a very large image database for image classification. It calculate the distance between the color combination extracted from the input image and the color combination of the database. The color combination with the smallest distance is the emotion of the image,consequently, the image belongs to the selected emotion category. As shown in Figure 11, the result is compare the emotions of the input images and 24 emotion schemes, and images with the same emotion will be classified into corresponding emotion schemes which were discussed in Section 3.1. This application can play an important role in image processing.


Figure 11. Color emotions for image classification. The table above in turn is our 24 emotion schemes, The process is to extract the color emotion of the picture, and then classify the picture into the emotion scheme that are closest to it.

## 7. CONCLUSION

In this paper, we proposed a novel style-transfer framework to change the emotions contained in a picture based on color combinations. Unlike traditional color transfer algorithms, users do not need to provide a reference image. Instead, the system will suggest the most suitable emotion palettes for the input picture, and the users simply choose the style they want to use to complete the style transfer for the picture. All results show that this approach can achieve many emotions for the photo. However, there are still several restrictions. First, the system cannot achieve real-time results. Although the system executes very fast, for larger pictures the speed must still be improved. Second, the color combinations suggested by the system are the closest emotions to the input image, which may not be the user's desired tones. Third, the system cannot measure the degree of emotion.

In view of the shortcomings of our system, in future work, we plan to solve these problems, create a new acceleration framework to achieve real-time results, provide users with more emotion-palettes to meet the needs of different tones, and quantify the connection between images and color themes. Our system can robustly transfer a variety of styles.

## ACKNOWLEDGE

This research was supported by the grant of National Science Foundation of China (No.61303147), Science Foundation of Hunan Province(No.2018JJ3064) , GPU grant programm from NVIDIA Corporation and HPCSIP Key Laboratory, Ministry of Education of China. We gratefully acknowledge the support of NVIDIA Corporation with the donation of the Titan Xp GPU used for this research.

## REFERENCES

[1] Reinhard, E., Ashikhmin, M., Gooch, B., \& Shirley, P. (2001). Color transfer between images. IEEE Computer Graphics \& Applications, 21(5), 34-41.
[2] C.-K. Yang and L.-K. Peng. Automatic mood-transferring between color images. IEEE Computer Graphics and Applications, 28(2):52 - 61, March-April 2008.
[3] Csurka, G., Skaff, S., Marchesotti, L., \& Saunders, C. 2010. Learning moods and emotions from color combinations. In Proceedings of the Seventh Indian Conference on Computer Vision, Graphics and Image Processing, ACM, 298305.
[4] Y Liu, C Michael, U Matt, R Szymon. AutoStyle: Automatic Style Transfer from Image Collections to Users' Images. Computer Graphics Forum, 2014 , 33 (4) :21-31.
[5] Pitié, François, A. C. Kokaram, and R. Dahyot.: Automated colour grading using colour distribution transfer. CVIU (2007).
[6] Chang, Y., Saito, S., Uchikawa, K., \& Nakajima, M.2005. Example-based color stylization of images. ACM Transactions on Applied Perception 2, 3 (July), 322345.
[7] Yoo, J. D., Park, M. K., Cho, J. H., \& Lee, K. H. Local color transfer between images using dominant colors. J. Electron. Imaging 22, 3 (July).
[8] Kanungo, Tapas, Mount, David, M., Netanyahu, \& Nathan, S., et al. (2000). The analysis of a simple k -means clustering algorithm. Proceedings of the Sixteenth Annual Symposium on Computational Geometry, 100-109.
[9] HS Park, CH Jun. A simple and fast algorithm for K-medoids clustering. Expert Systems with Applications, 2009, 36 (2):3336-3341.
[10] Cheng, Y.: Mean shift, mode seeking, and clustering. PAMI 17(1995)790-799.
[11]Comaniciu, D., Meer, P.: Mean shift: A robust approach toward feature space analysis. IEEE Trans. on PAMI (2002) 603-619.
[12] Tai, Y.W., Jia, J., Tang, K.: Local color transfer via probabilistic segmentation by expectation-maximization. Proc. CVPR 1, 747 (2005).
[13] Chang, Y., Saito, S., \& Nakajima, M. (2007). Example-based color transformation of image and video using basic color categories. IEEE Trans Image Process, 16(2), 329-336.
[14]Lin, S., \& Hanrahan, P. (2013). Modeling how people extract color themes from images. Sigchi Conference on Human Factors in Computing Systems (pp.3101-3110). ACM.
[15]H. Chang, O. Fried, Y. Liu, S. DiVerdi, and A. Finkelstein, Palette-based photo recoloring. ACM Trans. Graph., vol. 34, no. 4, p. 139, 2015.
[16] Q Zhang,C Xiao, HQ Sun,and F Tang.Palette-based image recoloring using color decomposition optimization. IEEE Transactions on Image Processing.2017,26(4): 1952-1964.
[17] Richard Zhang, Jun-Yan Zhu, Phillip Isola, Xinyang Geng, Angela S. Lin, Tianhe Yu, and Alexei A. Efros. Realtime user-guided image colorization with learned deep priors. SIGGRAPH, 2017.
[18] Ou LC, Luo MR, Woodcock A, Wright A (2004) A study of colour emotion and colour preference. Part I: Colour emotions for single colours. Color Res Appl 29(3):232-240. doi:10.1002/col.20010.
[19] Ou LC, Luo MR, Woodcock A, Wright A (2004) A study of colour emotion and colour preference. Part II: Colour emotions for two-colour combinations. Color Res Appl 29(4):292-298. doi:10.1002/col.20024.
[20]Kobayashi $S$ (1981) .The aim and method of the color image scale. Color Res Appl 6(2):93-107. doi:10.1002/col.5080060210.
[21] Wang, B., Yu, Y., Wong, T. T., Chen, C., \& Xu, Y. Q. (2010). Data-driven image color theme enhancement. Acm Transactions on Graphics, 29(6), 1-10.
[22] Kobayashi S (1991) Color image scale kosdansha international.
[23] Eisemann, L.: Pantone's Guide to Communicating with Color. Grafix Press (2000).
[24]http://www.colourlovers.com/.
[25]Grira, N., Crucianu, M., and Boujemaa, N. Unsupervised and semi- supervised Clustering: a brief survey. In A Review of Machine Learning Techniques for Processing Multimedia Content. MUSCLE European Network of Excellence, 2004.
[26] L He,H Qi,R Zaretzki.Image color transfer to evoke different emotions based on color combinations. Signal Image \& Video Processing, 2015, 9 (8):1965-1973.
[27]N Arbin,NS Suhaimi , NZ Mokhtar , Z Othman. Comparative Analysis between K-Means and K-Medoids for Statistical Clustering. International Conference on Artificial Intelligence, 2016:117-121
[28] Fujun Luan, Sylvain Paris, Eli Shechtman, and Kavita Bala. 2017. Deep Photo Style Transfer. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

