Emotion transfer for images based on color combinations

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Abstract

In this paper, an emotion transfer framework for color images based on color combinations is proposed. The purpose of emotion transfer is to change the “look and feel” of images. Colors are confirmed as the most important factor for “look and feel” of images. In addition, various studies in both art and science areas have concluded that other than single color, color combinations are necessary to delivery specific emotions. Therefore, we propose a novel framework to transfer emotion of images based on color combinations, using a predefined color emotion model. The contribution of this new framework is three-fold. First, users do not need to provide reference images as used in traditional color transfer algorithms. In most situations, users may not have enough aesthetic knowledge or path to choose desired reference images. Second, because of the usage of color combinations instead of single color for emotions, a new color transfer algorithm that does not require an image library is proposed based on color statistics. Third, again because of the usage of color combinations, artifacts that normally seen in traditional frameworks using single color are avoided. We present encouraging results generated from this new framework and its potential in several possible applications including emotion transfer of photos and paintings and colorization of gray-scale images.

Keywords: Emotion Transfer, Color Emotion, Color Combination, Color Transfer

1. Introduction

Among the many possible image-processing options, artists and scientists are increasingly interested in extracting “emotion” in images as well as changing the emotion by altering its colors. The pioneer work by Reinhard et al. \cite{1} made color transfer possible by providing a reference image. Later, various color transfer algorithms have been proposed. However, only until recently was the first emotion transfer algorithm proposed by Yang and Peng \cite{2}. Their work followed the tradition color transfer framework but added a single color scheme for emotions.

Color as an emotion messenger has attracted enormous interests from researchers in different disciplines \cite{3–9}. One may delight in the beautiful red and golden-yellow leaves of autumn, and in the magnificent colors of a sunset. The relationships between color and emotion is referred to as color emotion \cite{10}.

In our daily life colors are never seen in isolation, but always presented together with other colors. This is true when we look at our surroundings from the inside of a building to the entire cityscape \cite{7}. Therefore, it is inappropriate to apply single color scheme to identify the emotion in color images. For instance, in Kobayashi \cite{3}’s book Color Image Scale, “red” may have multiple meanings, such as rich, powerful, luxurious, dynamic and mellow, depending on what color it is combined with. In Eisemann \cite{5}’s book Pantone’s Guide to Communicating with Color, “orange” may indicate energizing, inviting, vital, friendly and tangy, “brown” may indicate rich, wholesome, durable, sheltering and rustic. Hence, color combinations are always preferred over single color to delivery specific emotions.

After Reinhard \cite{1}’s ground breaking work, color transfer algorithms have been extensively studied \cite{11–20}. Reinhard’s method is simple and efficient, but suffers from two problems. Firstly, it could produce unnaturally looking results in cases where the input and reference images have different color distributions. Secondly, as the algorithm is based on simple statistics (mean and deviation), it could produce results with low fidelity in both scene detail and color distribution \cite{16}.

Although there have been several methods proposed later that solved these two problems, they still need one or multiple reference images, while in most situations users may not have enough aesthetic knowledge to choose appropriate reference images and finding a correct reference image may become a time consuming task.

In this paper, we present a new emotion transfer framework based on color combinations that do not need reference images as used in traditional color transfer algorithms. Because of the usage of color combinations instead of single color scheme as in Yang and Peng \cite{2} for emotions, we also need to develop a new color transfer algorithm for emotion transfer purpose. The proposed emotion transfer framework allows users to select their desired emotion by providing keywords directly, e.g., “warm”, “romantic” and “cool”.

We adopt Eisemann \cite{5}’s color emotion scheme called Pantone color scheme that contains 27 emotions with each emotion containing 24 three-color combinations. This scheme is based on the early work of word association studies of color and emo-
and quantification [10]. Classification of single color emotion search topics in the study of single color emotion: classification and color combinations emotion. There have been two main re-

Related Work

2.1. Color Emotion

The rest of the paper is organized as follows. Section 2 re-
views previous work in related areas. Section 3 describes the proposed color combination-based emotion transfer framework in detail. Section 4 presents results and comparisons. Section 5 provides the discussion and future work.

2. Related Work

2.1. Color Emotion

Experimental studies of color psychology can be dated back to as early as 1894 when Cohn proposed the first empirical approach to color preference [22]. While a considerable number of studies have been conducted, findings from these early studies were diverse and tentative [23].

Recent models of color emotion include single color emotion and color combinations emotion. There have been two main re-

search topics in the study of single color emotion: classification and quantification [10]. Classification of single color emotion uses principal component analysis to reduce large number of colors to a small number of categories [3, 24, 6]. The quantifi-
cation of color emotion is studied firstly by Sato and Nakamura [24], later by Ou et al. [6] who provided a color emotion model with quantities on three color-emotion factors: activity, weight and heat. His study is then confirmed by Wei-ning et al. [9]. For color combinations, Kobayashi [3] developed a color emotion model based on psychology studies. Ou et al. [7] revealed a simple relationship of color and emotion that relies on single color emotion and color pair emotion. Lee et al. [25] used sets theory to evaluate color combinations. These early-stage studies on color emotion only consider color pairs.

In this paper, we adopt a color emotion scheme called Pan-
tone color scheme [5] for emotion transfer. Compared to single color emotion, color combinations provide a more appropriate and accurate way to describe color emotion in images.

2.2. Emotion Semantics of Images

Emotion semantics is the most abstract semantic structure in images, because it is closely related to cognitive models, culture background and aesthetic standards of users. Among all factors affecting the emotion of images, colors are confirmed as the most important factor [29]. Currently, there are two meth-

ods of extracting the emotion feature from an image. One is domain-based, which extracts relevant features based on special knowledge of the application field [27]. For instance, Itten [21] formulated a theory about the use of color and color combination in art and the semantics it includes.

The other method of extracting emotion features is to ana-
lyze which kinds of features have significant impact on users through psychology experiments. For example, Mao [28] proved that the fractal dimensions (FDs) of images are related to affective properties of an image. Tanaka [26] concluded that the contribution of color, spatial frequency, and size to attractiveness follows the order of color > size > spatial frequency, and the contribution of each feature heterogeneity to attractiveness follows the order of color heterogeneity > size heterogeneity > shape heterogeneity > texture heterogeneity. In this paper, we only consider color factors of emotions and rely on “color transfer” to achieve “emotion transfer”.

2.3. Color Transfer

We may classify existing color transfer methods into global and local algorithms, where “global” means the algorithm transfer colors using global statistic, e.g., global mean and global variance, while “local” means the algorithm transfer colors using different values for different regions of the input im-

age. The first global color transfer method was proposed by Rein-
hard et al. [11]. It shifts and scales the pixel values of the input image to match the mean and standard deviation of the refer-
ence image. This is done in the laβ opponent color space (CIELab), which is an average decorrelated space that allows color transfer to take place independently in each channel [29]. Other global approaches transfer high-level statistical proper-
ties. For example, Neumann and Neumann [10] used 3D his-
togram matching in the HSL color space and Xiao and Ma [16]...
Figure 2: Emotion transfer of an input image (a) to eight different emotions (b)-(i). The input image is an artwork called *A lonely house* made by Michael Otto, 2007.

used histogram matching in the $Ia\beta$ color space with the addition of using optimization to preserve gradients of the input image. Pitić et al. [14] proposed a method to transfer an N-dimensional probability distribution function to another. Li et al. [31] provided a color transfer method taking into consideration the weighted influences of the input as well as the reference image.

Although the CIELab color space is widely used in color transfer, there are other spaces that may work better. For example, using Independent Component Analysis (ICA) Grundland and Dodgson [32] computed a decorrelated color space that is based on the perceptually uniform CIELab color space and using approximate histogram matching to transfer the color between images. Xiao and Ma [15] decomposed the input and the reference image using Singular Value Decomposition (SVD) and transferred the pixels in the input image in a correlated space.

A general problem with global color transfer approaches is that if the structure of the input image and the reference image are vastly different, the results could look unnatural. Reinhard et al. [11] proposed a local method based on the inverse distance weighting to remedy the problem. Chang et al. [11] proposed a color transfer method whereby colors are classified into categories derived through a psychophysical color naming study. The color transfer then adheres to this classification by restricting resulting colors within their original categories in order to create a naturally-looking image [20]. Tai et al. [13] proposed a local transfer approach based on their soft color segmenta-

tion algorithm. Firstly, a modified EM algorithm was proposed to segment probabilistically by constructing Gaussian Mixture Models (GMM). Then the corresponding relationships were obtained to map each Gaussian component in the source image to some Gaussian in the reference image. Finally, Reinhard et al. [11]’s method was applied on each Gaussian component pairs. Chiou et al. [18] proposed a local color transfer algorithm based on intrinsic component. Dong et al. [19] proposed a fast local color transfer algorithm with dominant color mapping based on Earth Mover’s Distance (EMD). Huang and Chen [33] proposed a landmark-based sparse color representation for local color transfer.

There are several other color transfer algorithms. For example, Wen et al. [34] proposed a system for image enhancement by using a stroke-based color transfer algorithm. Welsh et al. [35] extended the idea of color transfer to colorize gray-scale images. Xiang et al. [17] developed a selective color transfer method with multi-source images. An and Pellacini [36] made the color transfer algorithm user controllable. Huang et al. [37] developed an example-based approach to transfer key color features from the template to the input image, where a color feature extraction algorithm, a post-processing technique and a color blending model is proposed to transfer a painting’s emotion to a real image.

The major difference between our approach and other color transfer methods not only resides in the color emotion model, but also that we do not need reference images. Therefore, existing color transfer algorithms may not satisfy the proposed
emotion transfer task. The algorithm developed by Huang et al. [37] involved emotion elements, however, they only considered warm and cool aspects of color emotions, while emotion in images need more complex color emotion model. A method relatively close to ours is proposed by Yang and Peng [2] which provided an automatic mood-transferring framework for color images. They used single color emotion scheme described in [4] to classify the input image to one of the 24 emotions. Firstly, they classified the input image in the RGB space. Next, they used method developed by Xiao and Ma [15] to transfer colors of the input image according to ten preselected images of a target emotion. They also used a local color adjustment technique to adjust the color emotion. Finally they selected the best output image using brightness and similarity between output images and the reference image. The major difference of our approach to this approach is we use color combinations rather than single color for emotions. In addition, we do not need an image library for emotions. Because of these two differences, a new color transfer algorithm is developed. In addition to the above differences, we also select the best output image in a different way since we do not use reference images.

3. Emotion Transfer

Figure 3 illustrates components involved in the proposed emotion transfer framework. Users can select target emotion by either providing a reference image or selecting an emotion keyword directly. If the user has a reference image, we can extract main colors in this image and compare the main colors to color combinations in the color emotion scheme. In this way the reference image is classified to a specific emotion. Either way, a specific emotion is selected and color combinations in this emotion are used for color transfer.

Meanwhile, main colors in the input image are also extracted. Once we have main colors in the input image as well as target color combinations, the color transfer algorithm transfers all colors in the input images to 24 output images (there are 24 three-color combinations for each emotion). The final step selects the best output image out of the 24. Details of each step are described in the following sections.

3.1. Color Emotion Model

The Pantone color scheme [5] contains 27 emotions with each emotion containing 24 three-color combinations. In total, there are 648 three-color combinations. The 27 emotions 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 and Unique 1-4. Every color combination in each emotion includes three colors: dominant color, subordinate color and accent color. The dominant color is the most important one and the accent color is the least important. For example, the color combinations of emotion “Playful” are illustrated in Figure 4. In each three-color combination, the center color is the dominant color, the “⊏” shape block is the subordinate color and the color shown in the right vertical bar is the accent color. All the colors in Pantone color scheme are in the CMYK space and we converted them to the CIELab space.

3.2. Main Colors Identification Using Clustering

In order to match the three-color combinations of the emotion model, we need to extract the dominant, subordinate and accent colors in the input image. If the user chooses to use a reference image, the same process needs to be applied to extract the main colors of the reference image. We adopt the Expectation-Maximization (EM) algorithm in the CIELab space.

We first convert the input image from the RGB space to the CIELab space. A D65 light source is assumed for conversions in both directions. Then, the k-means clustering algorithm is used to generate the initial three colors for the EM algorithm. When performing EM-based clustering, all clusters are modeled as Gaussian Mixtures where color statistics of each cluster is modeled by one Gaussian component. The three main colors are then identified as the mean of the three clusters.

We choose EM after comparing k-means, EM and improved EM [13], as shown in Figure 5. Compared to EM, a key limitation of k-means is its cluster model. The concept is based on
spherical clusters that are separable in a way so that the mean values of clusters converge towards the cluster centers. The clusters are expected to be of similar size, so that the assignment to the nearest cluster center is the correct assignment. EM is more flexible by taking into consideration of both variances and covariances of clusters. The EM result is thus able to accommodate clusters of variable sizes which are more suitable to this application. However, EM with random initialization suffers from the robustness problem which is resolved by EM with k-means initialization.

In addition, in order to transfer colors of the input image, we want to segment the image better in color-wise, not in object-wise. Comparing to the result of EM, the result of k-means segments the input image better in object-wise (it separates the sky and water precisely). However, because the color of the cloud in the sky are very close to the color of the water, the result of EM segment the input image better in color-wise. In the meantime, comparing to result of EM, the result of k-means merged the car lights and a part of the bridge into one region, while the result of EM segments the car lights and the bridge better in color-wise. In all, EM segments images better in color-wise. Because of this reason, the weights of Gaussian components in this algorithm can be naturally used as weights of the dominant, subordinate and accent colors.

We also implement the improved EM algorithm proposed by Tai et al. [13], in which the spatial information is added using bilateral filter after the expectation step in the EM algorithm. As shown in Figures 5 (d) and (h), Tai’s algorithm has better region smoothness because of the spatial filter. However, in many images we might not want this feature. For instance, result of Tai’s algorithm (Figure 5(d)) merged rocks with the ground and water surrounded into one region, while result of EM separated them. Therefore, EM is more suitable for clustering purpose because it segment image better in color-wise.

3.3. Emotion Classification

If the user provides a reference image, we classify the reference image to a specific emotion first. If the user directly selects the target emotion terms, e.g., “warm”, this step is not necessary. After identifying the three main colors in the reference image, a Euclidean distance measure is used to classify the emotion:

$$\min_i \sum_{j=1}^{24} \sum_{k=1}^{3} w_k \| C_{k}^R - C_{k}^{P_i,j} \|_2^2$$

where $i = 1, 2, \cdots, 27$ is the $i^{th}$ emotion of the 27 emotions in the Pantone color scheme, $j = 1, 2, \cdots, 24$ is the $j^{th}$ combination of the 24 color combinations in each emotion, $w_k, k = 1, 2, 3$ are weights of the $k^{th}$ cluster (Gaussian component) generated by the EM algorithm, $C_{k}^{P_i,j}$ is the three main colors in the reference image, $C_{k}^{R}$ is the $k^{th}$ color in the $i^{th}$ Pantone three-color combination of the $i^{th}$ emotion. Each color is a three-dimensional vector in the CIELab space.

Equation 1 sums up the distance between the three main colors in the reference image with the 24 color combinations in each emotion. The emotion with the minimum distance is identified as the emotion of the reference image.

3.4. Color Transfer

Now we have three clusters in the input image and a target emotion either specified by the user or identified in a reference image. Then, the emotion of the input image is transferred to the target emotion by the steps shown in Figure 6.

In this process, we use three guidelines to formulate the problem:

1. The transferred colors should still reside within the CIELab space, because if we transfer centers of clusters in the input image to some arbitrary colors, it may produce out of range values.
2. It is more important to guarantee the closeness between the transferred dominant cluster center to the dominant color in the Pantone color combination as compared to that of the subordinate or accent color.

3. It is well known that the human visual system is more sensitive to local intensity differences than to intensity itself. Thus preserving the color gradient is necessary to scene fidelity.

### 3.4.1. Calculation of Target Color Combinations

The first step in Figure 6 is to calculate target color combinations. Because in many situations, if we move the cluster centers of the input image to the exact Pantone color combinations, the output image may easily become out of range, we need to limit the movement of each cluster center so that the boundary colors in each cluster remain in the range of the color space. As we can see in Figure 7, if we move the cluster centers of the input image to the exact Pantone color combination, the resulting image (Figure 7) is darker than the input image. However, if we limit the movement of cluster centers, the resulting image (Figure 7) is almost at the same brightness level compared to that of the input image.

In order to limit the movement of cluster centers, we formulate the calculation of target color combinations as an optimization problem:

$$
\begin{align*}
\min_{\delta} & \quad f(\delta) = \sum_{k=1}^{3} w_k \left( C_{ij}^k + \delta^k - C_{ij}^k \right) \\
\text{s.t.} & \quad l_\alpha \beta_{\min} \leq (f_{\min}^k + \delta^k) \leq l_\alpha \beta_{\max}, \\
& \quad l_\alpha \beta_{\min} \leq (f_{\max}^k + \delta^k) \leq l_\alpha \beta_{\max}
\end{align*}
$$

(2)

where $C_{ij}^k, k = 1, 2, 3$ are the three cluster centers of the input image calculated by the EM algorithm, $w_k$ is the weight of each cluster (Gaussian component) also generated by the EM algorithm. $\delta^k$ is the movement of each cluster center. $C_{ij}^k$ are colors of the target Pantone color combination. $l_\alpha \beta_{\min}$ and $l_\alpha \beta_{\max}$ are the range of each dimension in the CIELab space. $f_{\min}^k$ and $f_{\max}^k$ are the minimum and maximum values of the $k^{th}$ cluster in each dimension, respectively. $C_{ij}^k, k = 1, 2, 3$ are colors of the target color combination.

This optimization problem is designed to satisfy the guidelines (1) and (2). The condition in Eq. 2 satisfies the first guideline, which guarantees all colors stay within range after color transfer. In addition, by minimizing the 2-norm distance in Eq. 2, target color combinations are moved as close as possible to desired Pantone color combinations. Weights $w_k$ put different weights on the dominant, subordinate and accent colors which helps the minimization process to consider more about the movement of the dominant color.

The interior point algorithm described in [40] is used to solve this optimization problem. For $\mu > 0$, the approximate problem is

$$
\begin{align*}
\min_{\delta, s} & \quad f(\delta, s) = \min_{\delta} f(\delta) - \mu \sum_{t=1}^{3} \sum_{i=1}^{4} \ln s^i_t \\
\text{s.t.} & \quad l_\alpha \beta_{\min} - (f_{\min}^k + \delta^k) + s^i_t = 0, \quad (f_{\min}^k + \delta^k) - l_\alpha \beta_{\max} + s^i_t = 0 \\
& \quad l_\alpha \beta_{\min} - (f_{\max}^k + \delta^k) + s^i_t = 0, \quad (f_{\max}^k + \delta^k) - l_\alpha \beta_{\max} + s^i_t = 0
\end{align*}
$$

(3)

where $s^i_t$ are slack variables. There are as many slack variables as there are inequality constraints. The $s^i_t$ are restricted to be positive to keep $ln s^i_t$ bounded. As $\mu$ decreases to zero, the minimum of $f_\delta$ should approach the minimum of $f$.

The approximate problem (Eq. 3) is a sequence of equality constrained problems. Waltz et al. [40] used two types of steps at each iteration to solve this problem, including a Newton step using linear approximation and a conjugate gradient (CG) step using a trust region.

Finally, target color combinations are calculated using Eq. 4:

$$
C_{ij}^k = C_{ij}^k + \delta^k
$$

(4)

### 3.4.2. Pixel Update

After calculation of target color combinations, the second step in Figure 6 updates all pixels in the input image. This process is done in each channel of $l_\alpha \beta$ independently. We update pixels using the method below:

$$
I_{xy}^l = I_{xy}^l - C_{ij}^k + C_{ij}^k
$$

(5)

where $I_{xy}^l$ and $I_{xy}^k$ are pixels of the $k^{th}$ clusters in the input and updated (intermediate) images, respectively.

### 3.4.3. Gradient Preservation

The final step in Figure 6 is gradient preservation. Let us first observe the differences in the transfer result without (Figure 7(d)) or with (Figure 7(c)) gradient preservation as compared to the input image (Figure 7(a)). We can see the artifacts in Figure 7(d), such as the edge between cloud and sky and the edge between water and sky. In addition, the contrast between the land and water is strong and the water is too bright. However, the transfer result with gradient preservation as shown in Figure 7(c) has no artifacts in edges and has average brightness and contrast compared to that of the input image. As required by guideline (3), preserving the gradient is necessary to scene fidelity.

To preserve gradient, we use the algorithm proposed by [16] where the formulation of problem is described as an optimization problem of

$$
\begin{align*}
\min_{\delta, s} & \quad f(\delta, s) = \min_{\delta} f(\delta) - \mu \sum_{t=1}^{3} \sum_{i=1}^{4} \ln s^i_t \\
\text{s.t.} & \quad l_\alpha \beta_{\min} - (f_{\min}^k + \delta^k) + s^i_t = 0, \quad (f_{\min}^k + \delta^k) - l_\alpha \beta_{\max} + s^i_t = 0 \\
& \quad l_\alpha \beta_{\min} - (f_{\max}^k + \delta^k) + s^i_t = 0, \quad (f_{\max}^k + \delta^k) - l_\alpha \beta_{\max} + s^i_t = 0
\end{align*}
$$

(3)
Figure 7: Steps in transferring to “Serene” emotion. (b) transfer without limitation of cluster center movement (c) transfer with limit of cluster center movement (d) transfer without gradient preservation step.

Figure 8: Pixel update and gradient preservation: Red, green and blue are convex hulls of dominate, subordinate and accent clusters, respectively. Cluster centers of the input image are connected by yellow lines and target cluster centers are connected by magenta lines. (a) correspond to the image of Figure 7(a) and (c) correspond to the image of Figure 7(c).

\[
\min_{O_{xy}} \sum_x \sum_y (O_{xy} - I'_{xy})^2 + \lambda \sum_x \sum_y [\left(\frac{\partial O_{xy}}{\partial x} - \frac{\partial I_{xy}}{\partial x}\right)^2 + \left(\frac{\partial O_{xy}}{\partial y} - \frac{\partial I_{xy}}{\partial y}\right)^2] \tag{6}
\]

where \(I_{xy}, I'_{xy},\) and \(O_{xy}\) are pixels in the input image, the intermediate image (image after updating all pixels), and the output image, respectively. \(x\) and \(y\) are the horizontal and vertical axes of the image. \(\lambda\) is a coefficient weighting the importance of gradient preservation and new colors.

The first term of Eq. 6 ensures the output image is as similar as possible to the intermediate image. The second term of Eq. 6 maintains the gradient of the output image as close as possible to the gradient of the input image. This optimization problem is solved by gradient descend method. Result of gradient preservation is also shown in Figure 8(c).

Xiao and Ma [16] set \(\lambda\) equal to 1 in their paper, however, the scene fidelity is not high enough in this application when \(\lambda = 1\). Impact of different \(\lambda\) values on color transfer result is demonstrated in Figure 7. Artifacts between the houses and the road reduce dramatically from \(\lambda = 1\) to \(\lambda = 20\), while the result images become similar when \(\lambda = 30\) and \(\lambda = 40\). We tested the impact of different \(\lambda\) values on color transfer scores (Eq. 9 in Section 3.5) and color transfer time. As illustrated in Figure 10, the score decreases (better) when \(\lambda\) value increases, and the score decrease fast when \(\lambda\) increases from 1 to 30. However, the color transfer time increases when \(\lambda\) increases. In order to balance the color transfer scores and time, we choose \(\lambda = 20\) in this paper.

3.5. Output Image Selection

When a user selects a specific emotion, we transfer the input image to 24 images based on the 24 color combinations of that emotion in the Pantone color scheme. The final step in the emotion transfer framework is to select the best output images by evaluating similarity of those images to the input image and distance of cluster centers to the Pantone color combinations.

To measure the difference in luminance between the input and output images, we use the following 2:
where \( I_{x,y} \) and \( O_{x,y} \) are the \( l \) values (in \( l\alpha\beta \) space) of the input and output images at pixel \((x, y)\), respectively. \( I \) and \( O \) are the input and output images, respectively. \( width \) and \( height \) represent the width and height of the input and output images.

To measure how close the cluster centers in the output image to the target Pantone color combinations, we use the following equation:

\[
d_{\text{color}}(C_{O,j}, C_{P,i,j}) = \sum_{k=1}^{3} |C_{O,j}^k - C_{P,i,j}^k| \tag{8}
\]

where \( C_{O,j}^k \) are colors in the target color combination (cluster centers in the output images) and \( C_{P,i,j}^k \) are colors in the target Pantone color combination. \( i = 1, 2, \cdots, 27 \) is the \( i \)th emotion of the 27 emotions in the Pantone color scheme, \( j = 1, 2, \cdots, 24 \) is the \( j \)th combination of the 24 color combinations in each emotion.

Finally, the best output image is selected by:

\[
\min_j E(j) = \gamma d_{\text{lumin}}(I, O_j) + (1 - \gamma) d_{\text{color}}(C_{O,j}, C_{P,j}) \tag{9}
\]

where \( j = 1, 2, ..., 24 \), and \( \gamma \) and \( 1 - \gamma \) are weighting factors to combine two types of differences into a unified metric. In our current implementation we set \( \gamma = 0.7 \), because we intend to emphasize more on the similarity of luminance. The image with minimum \( E(j) \) value is chosen as the final output image. Alternatively, we could sort all the output images by the corresponding \( E \) values and let users make the final decision.

4. Results and Comparisons

Our approach transfers the emotion of the input images using color combinations. Four applications of this approach are shown first in this section, including emotion transfer of an artwork, photos, a painting and colorization of gray-scale images. Next, in order to evaluate our technique, a comparison between emotion transfer method based on color combinations and the emotion transfer method based on single color is presented. At last, we compare our method with the traditional color transfer algorithms.

Emotion transfer. Figure 2 shows an example of emotion transfer of an artwork. The input image is transferred to eight target emotions, including Serene, Earthy, Romantic, Cool, Traditional, Robust, Classic and Spiritual. Figure 11 shows an application of emotion transfer on photos.

Figure 12 shows another application of our approach on paintings, where a painting shown in Figure 12(a) is transferred to seven alternative emotions.

The fourth application using the proposed emotion transfer framework is colorization of gray-scale images. Figure 13 shows the emotion transfer of an input gray-scale image (Figure 13(a)) to eight emotions, including Warm, Romantic, Traditional, Sweet, Cool, Unique, Natural and Delicate.

Comparison with the single color method. Figure 11 shows comparison of emotion transfer using color combinations and single colors. Emotion transfer using single color is implemented by moving the mean of \( l, \alpha, \beta \) values of the input images to the dominate color of Pantone color combination. Compared to the transfer results using single colors, results using color combinations have several advantages. Firstly, using color combinations to represent emotion of images allows color transfer to be carried out separately in different regions of images, producing more colorful and emotionally rich images. As shown in Figures 11(b) and (d), colors of the road, houses and trees are transferred to different colors separately.
Figure 11: Comparison of emotion transfer using color combination and single color. For 4 input images, each image is transferred to three emotions. Single colors are used for the upper three images and color combinations are used for the lower three images. The input images (a),(e),(i) and (m) are from the National Geography, http://photography.nationalgeographic.com/photography/wallpapers/
using color combinations, while those objects are transferred to similar colors using single color. Similarly, as shown in Figures 11(f) and (g), the colors of sky, lights near the ground and stones are transferred to different colors separately using color combinations, producing more colorful images compared to transfer results using single colors. Secondly, artifacts are eliminated using color combinations. For example, as shown in Figure 11(d), colors of the wall and trees are transferred to an unnatural look (green) using single colors, while colors of the wall and trees still look natural using color combinations. In Figure 11(o), colors of the grass in the middle are transferred to brown/pink using single color, while colors of the grass stay green using color combinations. Finally, using color combinations can avoid out of range problem. Transfer results in Figures 11(c)(d)(k)(l)(n) are too bright using single colors, while transfer results using color combinations successfully avoid this problem.

Comparison with color transfer. Although the purpose of our color transfer algorithm is different from traditional color transfer methods, we also compare our method (not including color emotion scheme) to three representative color transfer algorithms ([1, 16, 20]). If the user provides a reference image, the purpose of our algorithm is to transfer “emotion” in the input image to “emotion” of the reference image by changing colors, while the purpose of traditional color transfer methods is to transfer the “colors” in the input image to “colors” of the reference image. Figure 14 shows the color transfer results, with two input images (Figure 14(a)) and two reference images (Figure 14(b)). Compared to other methods, our method is able to blend the colors of the reference image, while preserving the look and details of the input image. For the first input image, Reinhard [1] and Xiao [16]’s results suffer from high color saturation in the trees region compared to that of the input image. Pouli and Reinhard [20]’s method suffers from losing gradient of the input image. Again, our method successfully avoids artifacts and maintain similar brightness level as compared to the input image.

5. Discussion and Future Work

In this paper, we proposed a novel emotion transfer framework based on color combinations. Unlike traditional color transfer algorithms, users are not required to provide reference images. They can choose target emotion terms and the desired emotion is transferred automatically. This process is achieved by using a color emotion scheme, in which each emotion is represented using 24 three-color combinations. We used the EM algorithm with k-means initialization as clustering algorithm in the CIELab space to identify three main colors of the input image. Then those clusters are transferred to new positions according to the target three-color combinations. For the color transfer algorithm, calculation of the target cluster centers is formulated as an optimization problem, followed by a pixel updating method and gradient preservation process. Finally, the best output image is selected using brightness similarity between the output images and the input image and a distance measure between transferred cluster centers and target Pantone color combinations.

Results showed our approach is able to alter emotion of photos and paintings, providing emotionally rich images for art and design purpose. In addition, our method can be used to colorize gray-scale images.

While our emotion transfer method can produce images that convey rich emotions, there are still several limitations. Firstly, using the EM clustering algorithm may result in unexpected
The number of clusters may be decided automatically as well. We used three clusters for each image, while in the future the number of colors may be used. Similarly, we included in the clustering algorithm. Secondly, current weights of the dominant, subordinate and accent colors are decided automatically by the weights of Gaussian components. However, in the situation shown in Figure 15, if colors of the flower are the dominant colors, it may not have the largest weight. Similarly, spatial information may need to be considered as a part of color weights. Finally, the first step of the color transfer algorithm described in Section 3.4.1 may result in cluster centers of the input image that do not have enough movement, depending on how colors are spread in the CIELab space and where those target Pantone colors are.

In the future, different color emotion models can be used in this framework, such as quantitative color emotion models. In addition, in this paper we only used three-color combinations, while adaptive number of colors may be used. Similarly, we used three clusters for each image, while in the future the number of clusters may be decided automatically as well.

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