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Texture-Aware Emotional Color Transfer Between Images

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ABSTRACT Different colors can evoke different emotions for images. For example, artists usually use different color combinations to express different emotions when creating posters or pictures. Existing color transfer methods can successfully transfer visual appearance between images by changing colors. However, they often fail to change an image to meet an accurate emotion. Nowadays, there are few emotional color transfer methods between images, and those methods are imperfect in transferring the emotion from one image to another image due to the inaccuracy in the emotion calculation of the reference image. Therefore, we propose a texture-aware emotional color transfer method between images, which can adjust an image with an emotion word or a reference image. Each emotion word represents a type of emotion, such as alluring, fresh, and antique. The user simply input an emotion word (e.g., lovely), the system can automatically adjust the image to the target emotion (e.g., fresh). First, we propose a new emotion calculation method to compute the target emotion from a reference image. Unlike previous methods, we take both texture features and main colors in our emotion calculation model. Then, in order to find the proper color combinations to reflect the target emotion, three color-emotion model databases are built by color numbers of the models. Those models are obtained by exploiting the famous art theories, and we design a novel strategy to select the most suitable color-emotion model from the databases. Finally, we propose a new color transfer algorithm by utilizing color adjustment and color blending to guarantee the color gradient and naturalness. Experiments show that our method's results are more consistent with the emotion of the input image than the state-of-the-art algorithms.

INDEX TERMS Image emotion, emotion calculation, color transfer, color-emotion model.

I. INTRODUCTION

Emotions play an important role in how we think and behave. Understanding the characteristics of emotions can help us know how people's emotions influence their activities [1], [2]. Meanwhile, the booming needs for editing these pictures emerge. Among many possible image-processing options, users have become more and more interested in changing an image's tone or emotion by altering its colors. Designers who understand color-emotion can create some better works. However, some image processing softwares such as Photoshop cannot be used to edit an image directly to meet a desired emotion.

In recent years, researchers have intensively studied how to convey opinions by editing the colors of an image, such as color transfer [3]–[6], image recoloring [7], [8], and color enhancement [9]–[11]. Those methods all aimed at transforming the appearance of image by changing colors. However, they cannot directly change an image to meet an accurate emotion. More recently, some scholars began to study emotion-based color transfer techniques [12], [13], i.e., editing images through some colors or color combinations to convey emotion. Wang *et al.* [12] proposed a new method which can automatically adjust image color to meet a desired emotion by giving an emotion word. Yang and Peng [13] presented a method for transferring mood between color images. He *et al.* [14] proposed a color transfer framework to evoke different emotions for images based on color combinations. These methods focus on changing the emotions of images through a single color or color combinations. However, they only considered colors and ignored the influence of texture. Texture features also produce significant effect and cannot be neglected [15]. Furthermore, they all used color combinations with a certain number, ignoring the difference of hue number (HN) in the target images.

As a result, those methods may generate wrong colors in the transfer results, which may deviate from the target emotion. In this paper, we propose a new color transfer framework in which users only need to provide a reference image or input an emotion word. When computing emotion values of the reference images, different from the previous methods, we consider both main colors and texture features. This makes the results of emotion calculation more accurate. We build three color-emotion model databases based on the theories and work in Kobayashi et al.'s methods [16]. In those databases, color-emotion models are separated into three groups by the color number (CN) of models. According to the CN of target image we use hue harmonious models to dynamically choose color-emotion models from databases. Finally, we propose a new color transfer algorithm by utilizing color adjustment and color blending to guarantee the color gradient and naturalness. The main contributions of our work can be summarized as follows:

(1) We design a texture-aware emotional color transfer framework, which can change an image's colors to meet a desired emotion calculated from a reference image or an emotion word.

(2) We propose a new emotion calculation model to obtain the target emotion from a reference image considering both main colors and texture features.

(3) A variable-color-number model selection method for reflecting the target emotion is designed to select the most suitable color models from the predefined databases.

II. RELATED WORK

A. COLOR TRANSFER

The automatic color transfer algorithm between images was first proposed by Reinhard *et al.* [3]. Since then, it is possible for color transfer with reference images. This method was based on statistics and was extended to grayscale image in by Welsh *et al.* [4] Later, several different color transfer algorithms have been proposed [17], [18]. Chia *et al.* [7] proposed an colorization method based Internet with a user given segmentation mask and text labels. Wang *et al.* [10] developed an interesting method for color and tone adjustment from examples. Yoo *et al.* [18] applied a statistical transfer method by finding local region correspondences between two images. Though those methods may convey specific emotions in transfer results, finding a reference image with both similar appearance and the desired emotion is really a tough job. Besides those color transfer methods, some other techniques can also change images appearance with reference images or color combinations, such as image recoloring and image enhancement. A recent work in [8] described a palette-based recoloring method which allowed users to choose colors to recolor images. Wang *et al.* [9] adopted the edit propagation method to obtain a soft segment and recolor an image to meet a color combination.

In recent years, with the rise of deep learning, its framework makes feature learning more accurate. The convolutional neural network (CNN) consists of several convolutional layers and several fully connected layers. Lizuka *et al.* [19] proposed a CNN-based image colorization framework. This framework uses an end-to-end approach to train the neural network. And the framework can handle images of any resolution. However, this is a data-driven method. Therefore, it is only applicable to images that similar to the training set. Yan *et al.* [20] proposed a deep neural networks framework to adjust photoes, and introduced the context descriptor to analyze the semantics of the image. Jing *et al.* [21] summarized the progress of the current neural style transfer and discuss its problems. Kim *et al.* [22] proposed a method based on generative adversarial network that can successfully transfer style from one domain to another while preserving key attributes such as orientation and face identity.

These methods do not consider emotion of the image. For the emotional color transfer method, it is very important to model the emotion of the image. However, there is no successful method to model emotions using neural networks. The existing experimental results of the CNN-based image edit method are relatively good. Moreover, it is difficult to model the emotion of images. The existing image emotion databases contain a small number of pictures. For deep learning networks, large-scale datasets are needed for precise training. There is not enough data. In contrast, the traditional method has been successful in the modeling of emotion calculation. Therefore, in this paper, we employ hand-crafted techniques.

B. EMOTION BASED COLOR TRANSFER

The first emotional color transfer method was developed by Yang and Peng [13], which followed the traditional color transfer framework. But this method added only a single color scheme for emotions. Then Wu *et al.* [23] presented a content-based color transfer method that utilized subject area detection and surface layout recovery to minimize user effort which can produce great results. Later, Ryoo [24] proposed an emotion color transfer method. They used the feature based facial expression recognition to recognize human emotion and then mapped the color palette of the input image to the emotional color palette. These two methods only considered a single color to represent an emotion. In addition to a single color, color combinations are more necessary to evoke specific emotions. Recently, He *et al.* [14] raised a color transfer framework to evoke different emotions for images based on 3-color combinations in [25]. However, this method contained only 27 emotion words. This is not enough to express human emotion. In addition, when calculating the emotion value of reference image, they only considered color features. However, the texture features also affect the emotion value, which should not be ignored. Wang *et al.* [12] proposed a complete system that automatically adjusted image color to meet an affective word. They adopted a 5-color theme to describe the image color composition and built a database that contained more than 400,000 color themes with emotion words. They only changed an image's emotion based on an emotion word, and did not deal with reference image

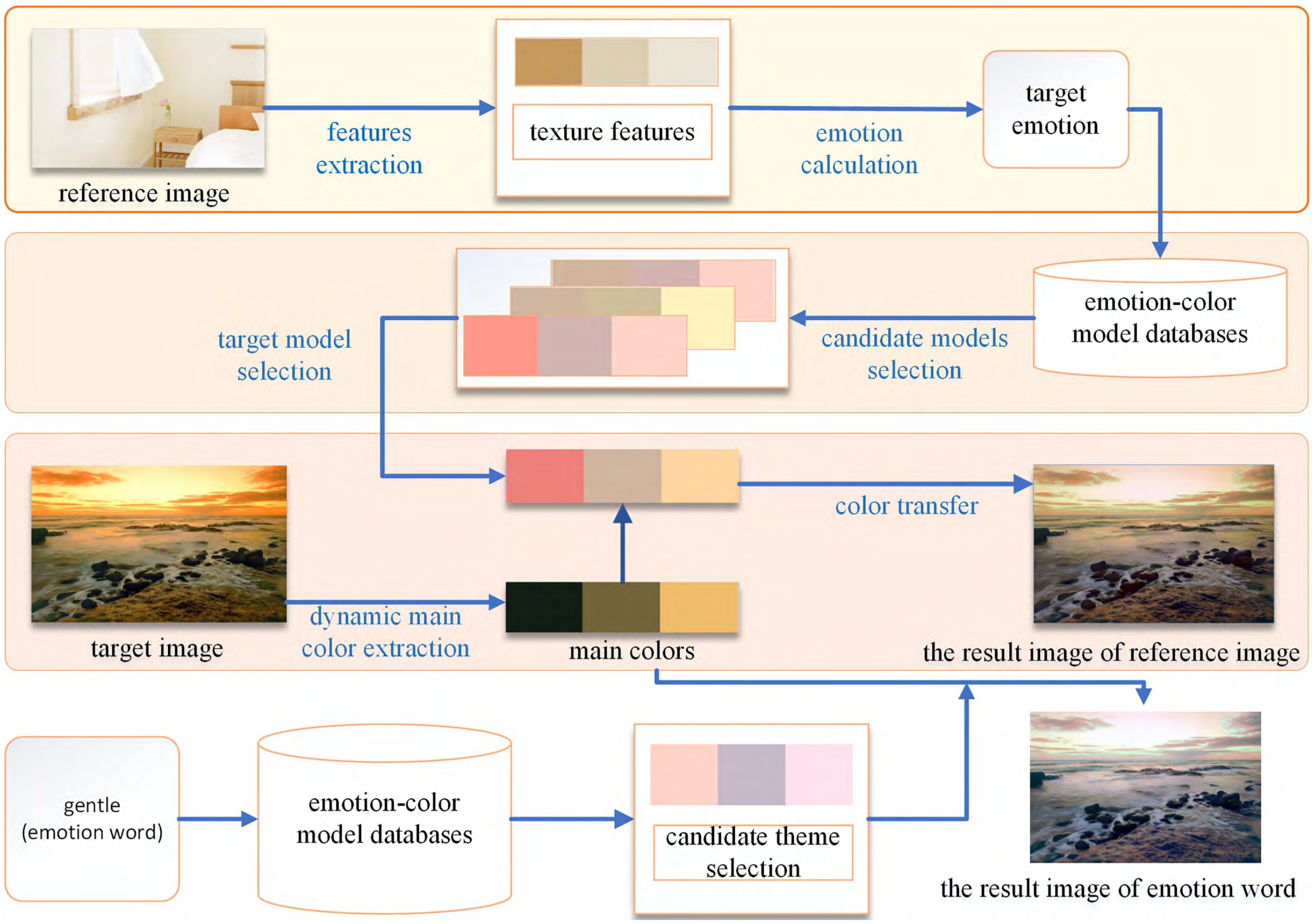


FIGURE 1. The framework of texture-aware emotional color transfer method between images.

based emotional color transfer. In addition, those color transfer methods chose either a fixed number of color combination or a single color. This strategy may not suit for target images with different amounts of colors. Peng *et al.* [26] thought that different people have different understanding of image emotion. If the emotion that represents the image is emotional distribution, the emotion of an image can be expressed objectively. Thus, Peng *et al.* [26] changed the way that simply predicting a single dominant emotion in the past, but used deep learning to predict the emotion distribution of images and established a new database, Emotion6. However, this method cannot be applied to all images. For some high-level semantic images, the resulting image appears artifacts after emotional color transfer.

III. OVERVIEW

The overall pipeline of our framework is shown in Figure 1. Our method is divided into three main steps. First, if the input is a reference image, we start from extracting the main colors and texture features of reference image. These features and colors are used to calculate the target emotion coordinate value in emotion scales by a new emotion calculation model we proposed. If the input is an emotion word, we use the standard semantic similarity algorithm to obtain the nearest landmark word defined in the databases and regard it as the target emotion. After that, we search the emotion database and find the most matching target emotion. These databases are built by exploiting the theoretical and empirical concepts in famous art theories that contain color models, corresponding emotion coordinates, emotion words as well as HN and CN. Note that, we have three databases that contain different CN of those models. Then we get the closest color combinations from one of the model databases. Next, we propose a new model selection strategy to get a target model. Then, we can get the candidate color combinations. Finally, we adjust the input images by designing a novel color transfer method.

IV. EMOTION CALCULATION FROM THE REFERENCE IMAGE

Several color transfer methods have been developed to change image's emotions by providing reference images [13], [14]. However, they only considered the colors of reference images. Among the factors that influence the image emotion, texture features produce significant effect and cannot be ignored. Table 1 shows the comparison of

TABLE 1. Comparison of the performance (adjusted R^2).

Emotion Scale	Color Function	Texture-Color Function
Warm-Cool	0.82	0.84
Hard-Soft	0	0.73

emotion calculation model performances between the color function and color joint texture function in Lucassen et al.'s research [15]. The adjusted R^2 as a goodness-of-fit measure for the regression functions. The adjusted R^2 of color joint texture models is higher than color models. In this study, we propose a new emotion calculation model to obtain the target emotion from a reference image by considering both main colors and the texture features based on Lucassen et al.'s work [15].

A. EMOTION CALCULATION

Lucassen *et al.* [15] claimed that texture fully determined the responses on the hard-soft scale, and played a role of decreasing weights for the masculine-feminine, heavy-light, and warm-cool scales. They proposed a function to predict the absolute scale values of color and texture emotions. Besides, according to Lucassen et al.'s work, the performance of this function is superior to Xin and Cheng's method [27] and Ou et al.'s method [28]. For the scales of warm-cool and hard-soft, the adjusted R^2 is higher than other two methods. We adopt this model to calculate the scale values of color and texture emotion. The most famous two-dimensional system being widely used in art design, [16] is the image-scale space with two dimensions: warm-cool scale and hard-soft scale. And the color-emotion models in this paper are mapped into those two scales. Therefore, we just calculate the emotion coordinate of reference image in the warm-cool scale and the hard-soft scale.

Lucassen *et al.* [15] used textures that were synthesized on the basis of Perlin noise. The calculation of the emotion value of the reference image is divided into three steps. Firstly, we compute the Gabor features and store those features of each Perlin texture images on the offline phase. Then, we extract the texture features and the main colors of reference image and find the best matched Perlin textures to get the Perlin parameters by Gabor texture features. Finally, we use the Perlin parameters and main colors to calculate the scale values in warm-cool and hard-soft scales. The function is derived from a group averaged scale values. A negative scale value indicates a response toward the left word of the opposite word-pair (e.g., warm on the warm-cool scale), and a positive value denotes a response to the right word (e.g., cool on the warm-cool scale). Zero corresponds to the center of the scale which represents a neutral response, i.e., neither warm nor cold on the warm-cool example. The function predicts the activity on the emotion scales based on the CIELAB color parameters $L*$, $C*$, h, and the Perlin noise texture parameters (oct, number of octaves; $freq$, frequency; $pers$, persistence; lac, lacunarity):

$$WC = -0.8 + 0.015L - 0.2C^{0.65} cos(h-40) + 0.056oct \tag{1}$$

$$\begin{aligned} HS = {} & 586.33 - 178.78oct^{0.01} - 84.20freq^{0.01} \\ & - 106.83pers^{0.02} - 213.89lac^{0.01} \end{aligned} \tag{2}$$

where WC and HS denote the warm-cool and hard-soft scales, respectively. The parameter value represents the change weight of the color-emotion.

B. DYNAMIC MAIN COLOR EXTRACTION

Previous methods extracted main colors with a fixed CN, which was determined by the color-emotion models. For example, Wang *et al.* [29] used five dominant colors in HSV color space to calculate image's emotion value. However, the colorful degree of each image is different and color models with fixed CN cannot fit all kinds of images. Therefore, the CN of the target color model should match the input image. In this section, we propose a new image segmentation method and a new main color extraction method which can dynamically determine how many colors should be included in the main colors.

1) DETERMINING THE COLOR NUMBER

Matsuda [30] summarized eight harmonious models that demonstrated eight distributions of hue. These models can measure the relative relationship of colors. However, the histogram can only measure the color distribution. Therefore, we select these models rather than the histogram. These models were widely used in the field of color measurement and color design [31], [32]. By analyzing those models, we can indicate approximately how many colors they contain. Inspired by those models and considering the CN of models in databases, we summarize a hue model-color number relationship. The relationship is shown in Table 2, where $Type = i, \ldots, N$ is the hue model type in [30]; HN_c and CN_c denote the hue number and color number of main colors C in a image. Correspondingly, we use HN_T and CN_T to indicate the hue number and color number of color-emotion models in databases. Then we employ the method proposed by Li and Chen [33] to measure the distance between the histogram and the model, so as to find the most suitable model.

TABLE 2. Hue model-color number relationship.

Type	i	V	L	I	T	X	Y	N
HN_c	1	2	3	4	4	5	5	6
CN_c	3	3	3	5	5	5	5	7

We then match those models using the method proposed by Li and Chen [33]. We use $H(x, y)$ to represent hue of pixel (x, y) and use $T_n(\alpha)$ to denote the nth model rotating α degree.

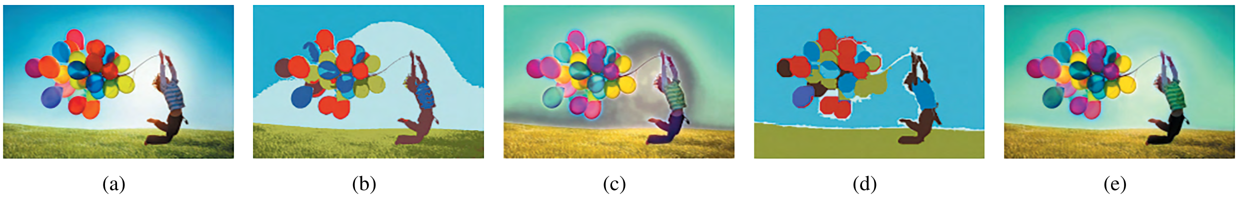


FIGURE 2. The comparison of segmentation results and color transfer results. (a) is the source image, (b) is the segment result using K-means method, (c) is the color transfer result using segment result in (b), (d) is the segment result using our method, and (e) is the color transfer result using our segment result in (d).

We match an image with the model $T_n(\alpha)$ as follows:

$$E_{T_n(\alpha)(x,y)} = \begin{cases} H(x,y) & H(x,y) \in G_n \\ H_{nearest\_border} & H(x,y) \notin G_n \end{cases} \tag{3}$$

where $E_{T_n(\alpha)}(x,y)$ indicates the hue value which is close to the hue of pixel (x,y) in $T_n(\alpha)$, G_n is the gray region of nth model and $H_{nearest\_border}$ is the border nearest pixel (x,y) in this model. Then the distance of model and hue histogram can be defined as:

$$F_{n,\alpha} = \sum \sum ||H(x,y) - E_{T_n(\alpha)}(x,y)|| \tag{4}$$

where $|| \cdot ||$ is the arc distance of hue circle. Finally, we minimize $F_{n,\alpha}$ to seek the parameters (n,α) by the following formulas:

$$\alpha(n) = \arg\min_{\alpha}(F_{n,\alpha}) \tag{5}$$

$$n_0 = \arg\min_{\alpha}{}_n(F_{n,\alpha}), n_0 \in \{1,2,\ldots,8\} \tag{6}$$

where n_0 is the model best-matched with the image hue. However, some model may be included in another model, e.g., if an image fits i-type model, it can also fit the other models. In order to ensure the uniqueness of the matching, we employ the descending strict degree ordering proposed by Li and Chen [33]: $St(i) > St(I) > St(V) > St(Y) > St(L) > St(X) > St(T) > St(N)$, where $St(\cdot)$ is the strict degree of the model. Next, we would identify the main colors of the reference images and the target images.

2) IMAGE SEGMENTATION AND MAIN COLOR EXTRACTION

Generally, most of the image segmentation methods may segment objects in an image into discrete units. For example, the sky is divided into two parts in Figure 2(b), which may cause the two parts being assigned different target colors, like green and gray in Figure 2(c). In order to solve this problem, we propose an image segmentation method based on object segmentation and main color extraction. We treat each unit part of the image as a whole when the color is divided, so that no scattered unit parts are present. We use the object-based segmentation method in [34]. The method first creates an undirected graph $G = (V, E)$ for the input image. Each pixel of the image corresponds to a node $v_i \in V$. The distance difference between two pixels in HSV space is the weight $w(v_i, v_j)$ of the edge $(v_i, v_j) \in E$ between each two nodes. In the graph-based segmentation method, a segment S is a division of the node set V. Each component or each region $C \in S$ corresponds to a graph $G'' = (V, E')$. Here $E' \in E$. Then we define the internal difference $Int(C)$ for each block. And the $Int(C)$ is taken as the maximum weight of the node C in the minimum spanning tree. The edges in the graph are sorted in ascending order. If the boundary values of the two regions are less than $Min(Int(C_1) + \tau(C_1), Int(C_2) + \tau(C_2))$, the regions C_1 and C_2 are merged, where $\tau(R) = K/|R|$, and k is the combined scale factor used to adjust the size of the merged block.

After the object-based segmentation result is obtained, the results of the over-segmentation are clustered in the CIELab space to produce the final segmentation graph. In the CIELab space, the color is divided into three channels, where a, b is the hue channel and L is the luminance channel. It is very sensitive to the perception of hue when the human eye distinguishes colors. Therefore, we add a weight to the three channels during clustering. For a given set of pixels $(x_1, x_2, \ldots, x_n)$, the image is expressed as P, and the K-means clustering is intended to find a division of all pixels to k $(k <= n)$ sets expressed as C: $C_i = \underset{S}{argmin} \sum_{i=1}^{k} \sum_{x \epsilon S_i} w \|x - \mu_i\|^2$, where $x \epsilon P$, μ_i is the mean of each set S_i, w is the weight vector of $3D$, $k = CN(C)$. $CN(C)$ is shown in Table 2. For parameter w, we set the a and b channel weights of 1, respectively. And we set the weight of the L channel to be w_l. Then, $w = (w_l, 1, 1)$. Usually the smaller the difference in the hue difference, the stronger the ability to distinguish the L channel when distinguishing the color. Therefore, the weight of the L channel is related to the hue difference. Here, the hue value of the image in L channel is calculated, and then the pixel with a higher L occurrence frequency can be obtained by covering 90% of the image.

V. SELECTION OF THE TARGET MODEL

As an emotion can be expressed by multiple color combinations, we design a new strategy to select the most suitable color models from candidate emotion models in this section.

A. COLOR-EMOTION MODEL DATABASE ESTABLISHMENT

In order to facilitate our following work, we build three color-emotion model databases that contain 1170 3-color combinations, 490 5-color combinations, fourteen 7-color combinations as well as corresponding emotion words and the emotion coordinate values in warm-cool and hard-soft scales. We divide those models into groups by HN of each color combinations based on the theory in [16]. Kobayashi [16] created a color system, in which the colors were divided into

10 hues such as red, orange, yellow etc., and 12 tones in each hue, as well as 10 neutral colors. We calculate the HN in each color model and denote as HN_T, where T is a color model in the database.

B. SELECTION OF THE TARGET MODEL

For an emotion word extracted form reference image or user input directly, we fetch its most proximate landmark words in emotion model databases. WordNet [35], [36] is a large lexical database of English, in which it groups words together based on their meanings. We calculate the similarity between the given word and landmark words based on WordNet and choose the most suitable landmark words. Then we get all the color-emotion models of those landmark words from one database. For a reference image, since we have the emotion coordinate of reference image in emotion space and the color-emotion models in databases, we can directly fetch a few of closest models.

Here, we formulate three principles for the models selection. First, when there exist reference images, the selected models should be similar to the reference images as far as possible. Second, if the user input is an emotion word, the selected models should be similar to the target images. Finally, the HN of model colors should match the target images, which is shown in Table 1. To satisfy the three principles, we select five most suitable models from candidate models by the following formula:

$$\underset{T'_i \in perm(T_i)}{\arg\min} \; \alpha_1 \sum_{j=1}^{k} D({t'}_{i,j}, s_j) + \alpha_2 R(HN_C - HN_{T'_i})$$

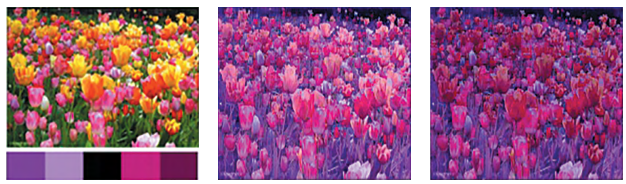
$$R(HN_C - HN_T) = \begin{cases} 1 & HN_C - HN_T = 0 \\ 2 & HN_C - HN_T = 1 \\ 3 & HN_C - HN_T = -1 \end{cases} \tag{7}$$

where $T'_i = \{t_{i,1}, t_{i,2}, \ldots, t_{i,k}\}$ is the set of model colors, and k is the number of main colors (CN_C); $perm(T_i)$ denotes the 120 permutations of the k-color model T_i; $c_j \in C$ and S_j are the main colors in source image and reference image; D is the Euclidean distance of the two colors and we normalize D to $[0, 1]$. The first term and the second term represent the similarity of candidate color models and main colors of input image and main colors of reference image, respectively. The last term is to match the HN between model colors and main color of target image. To reach the first two principles, we set $(\alpha_1 = 0, \alpha_2 = 1)$ when there exists reference image, and $(\alpha_1 = 1, \alpha_2 = 1)$ when the reference image does not exist. And the emotional coordinate is in the range of $(-5, 5)$ by the emotion calculation model and quantifies the coordinate values to $(-1, 1)$, due to $HN_C - HN_T = \{-1, 0, 1\}$

VI. EMOTIONAL COLOR TRANSFER

A. THE OPTIMIZATION OF TARGET MODEL

When there are large gaps between main colors and model colors in brightness and saturation, simple color transfer methods may lead to unnatural results. To alleviate this problem, we adjust two channels (brightness and saturation) of the target model in HSV color space. We constrain the relative ordering of brightness between the main colors and model colors. To change the brightness of a model, we simply modify the V channel in HSV space. First, we sort the main colors by brightness and get the result $C(I)$, and we have to make sure that $V_{C_i} > V_{C_j} (i > j)$, and the model colors are arranged by the same order I. For the model colors, we also want to ensure $V_{T_i} > V_{T_j} (i > j)$ and hope that the gaps of brightness in every two corresponding colors $V_I = V_{C(I)}$ are as similar as possible. We get the min value of those gaps and express as $mi = \min(|\Delta V_I|)$, then the new model is calculated by $T'(I) = V_{T(I)} + \delta \times \Delta V_I + mi$, where $\delta\,(0 \sim 1)$ is a coefficient representing the degree of model colors shift of the main colors. And the smaller δ is, the less the distance of new colors with model colors will become. On the contrary, the new colors are closer to main colors. In our experiments, we set 1 and 0 to be the coefficients in brightness and saturation, respectively. Figure 3 and Figure 4 show the importance of adjusting saturation and brightness, respectively.



(a) (b) (c)

FIGURE 3. The results of brightness optimization. (a) is the input image and color combination, (b) is the transfer result with brightness adjustment, and (c) is the transfer result without brightness adjustment.

(a) (b) (c)

FIGURE 4. The results of saturation optimization. (a) is the input image and color combination, (b) is the transfer result with saturation adjustment, and (c) is the transfer result without saturation adjustment.

B. COLOR TRANSFER

Since we have completed the adjustment of brightness and saturation of target model colors, in this section we use the modified colors to recolor the target image. We propose a new color transfer algorithm to ensure naturalness of the result images and introduce gradient preservation to guarantee smoothness.

Our algorithm is designed to satisfy two guidelines. First, we make sure that the colors changing to the same color in one block, i.e., maintain that the target color of each pixel is similar to other pixels in one block. Second, pixels with similar colors are more likely to receive similar amount of adjustment. Thus, we propose a new color transfer method based on color blending to meet the two principles. The new color $f(p)$ of each pixel p is computed as follows:

$$f(p) = x + \sum_{i}^{k} \theta_i (C_i - T_i') \tag{8}$$

where k is the number of main colors (CN_c), and θ_i is the color variation coefficient of each pair of main color and new model color, written as:

$$\theta_i = \lambda_i \frac{1}{D(p - C_i)} \tag{9}$$

where λ_i represents the importance of block i and it is designed for the first principle, and D is the Euclidean distance. If p belongs to block i, we set $\lambda_i > 1$ ($\lambda_i = 3$ in our experiment); otherwise, we set $\lambda_i = 1$. At last, we use $\sum_{i=1}^{k} \theta_i = 1$ for normalization.

To guarantee the smoothness of the output image, we carry out the final operation namely gradient preservation. We use the algorithm proposed by Xiao and Ma [37].

C. EVALUATION

To evaluate the results of our method, we design an evaluation model. Since there is a mapping between the main colors combination and emotion, we can calculate the emotional values. When there are large gaps between main colors and model colors in brightness and saturation, naive transfer may lead to unnatural results. We calculate the emotion values of the results using an emotion calculation model and get the distance with the input emotion. The smaller the distance is, the better of the result is. To maintain balance (fairness) in different methods, we use a third-party calculation model to get the emotion value of result image, that is Ou et al.'s method [28]. We extract the main color of the result images using the K-means method and then calculate the emotion value (warm-cool and hard-soft) using Ou et al.'s method. The final emotion value E_r of the result image is determined by

$$E_r = \frac{1}{N} \sum_{i=1}^{k} (|P_i| \times E(P_i)) \tag{10}$$

where $E(P_i)$ is the calculation model in Ou et al.'s method [28], P_i is the clusters generated by K-means, $|P_i|$ is the pixel number of P_i and N is the pixel number of the whole image.

VII. EXPERIMENTS AND RESULTS

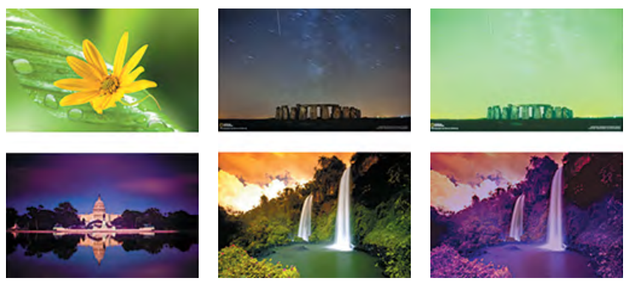
We tested our new method on a PC equipped with an Intel Core i5 4460, Nvidia gtx745ti display card, and 8G RAM. On average, the runtime of images with resolutions of 500 × 300 and 1024 × 786 are 0.271 seconds and 0.746 seconds, respectively. Fifty different images were processed for each emotion through emotional color transfer. The image data comes from He et al.'s method [14]. Then we carry out the emotion calculation and get 180 emotional classification, the total amount of data is 9000. In this section, we evaluate our method in five ways. Section VII-A discusses the time complexity of our method. Section VII-B directly compares our approach with some existing methods in the literature. Section VII-C shows the results of emotional color transfer without adding texture and adding texture under the same target color combination. Section VII-D compares our approach with other state-of-the-art methods. Section VII-E presents a user study in which we ask non-professional users who are not familiar with image editing software (e.g., Adobe Photoshop) to use our method and He et al.'s method as a baseline.

A. TIME COMPLEXITY ANALYSIS

Our method can be divided into three main steps, i.e., dynamic main color extraction, the target model selection, and color transfer. The time complexity of the first step is $O(nlogn)$ which is also fast in practice, general running in a fraction of a second. n is the number of the image pixels. The time complexity of the second step is $O(log(C))$, where C is the number of main colors in the source image. The time complexity of the third step is $O(n)$.

B. EMOTIONAL COLOR TRANSFER RESULTS

Figure 5 demonstrates the emotional color transfer results with reference images. It can be seen from Figure 5 that by taking into account the emotions of the source image, the results seem more natural. Figure 6 shows a comparison between our method and Wu et al.'s method [23]. It can be seen from Figure 6(d) that Wu et al.'s method does not greatly express the color of the sky. By contrast, since our method focuses on the color of the source image and the sensitivity of the reference image, it can produce plausible result where the brightness and textureness is better than that of Figure 6(d).



(a) (b) (c)

FIGURE 5. The results of emotional color transfer with reference images. (a) reference. (b) source. (c) result.

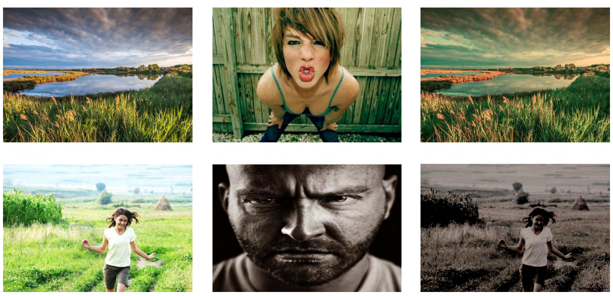
(a) (b) (c) (d)

FIGURE 6. Comparison with Wu et al.'s method [23]. (a) reference. (b) source. (c) our method.

Figure 7 shows the emotional color transfer results by inputting different emotion words. The input images are transferred to three target models, including alluring, fresh, and unique.

FIGURE 7. The results of emotional color transfer with emotion words.

We show some typical failure modes of emotion transferring in Figure 8. The emotion of the reference image in the first row obtained by our method is Fresh. However, the emotion of the reference image should be angry. When the reference image contains high-level semantics, our method is ambiguous. This is also mostly caused by the high level semantics such that copying the low-level features of the target cannot totally replicate its emotional stimuli. In the future work, we will improve the method by conducting a more detailed analysis of the emotions of the target image.



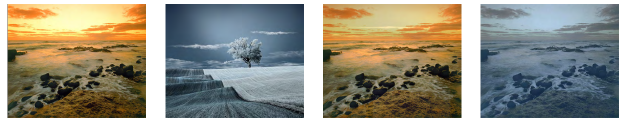
(a) (b) (c)

FIGURE 8. Failure examples of transferring image emotion. (a) source. (b) reference. (c) result.

C. VALIDATION OF THE EFFECT OF IMAGE TEXTURES

In order to prove the necessity of texture factors, we use Gabor wavelet transform to extract the texture features of the image, and use the texture feature to match Perlin texture to obtain Perlin texture parameters oct, $freq$, $pers$ and lac. By controlling the four parameters, oct, $freq$, $pers$ and lac, we can obtain random texture samples. In our experiments, we created $100,000$ texture samples.

Figure 9 shows the results of emotional color transfer without adding color and adding color under the same target image. As can be seen from Figure 9, without adding color features, our method can add texture of the target image to the source image. However, the hue of the source image does not change. Figure 10 shows the results of emotional color transfer without adding texture and adding texture under the same target color combinations. As can be seen from Figure 10, without adding a texture, the image shows a green color block in the sky, and some textures are lost, and the building in the middle of the image appears green. In contrast, by adding the texture, the color of the image in the resulting image keeps the color of the building in the middle of the image, which is consistent to human's emotional cognition.



(a) (b) (c) (d)

FIGURE 9. The validation result of the effect of image color. (a) is the input image, (b) is the target image, (c) is the result without adding color, and (d) is the result generated by adding color.

(a) (b) (c)

FIGURE 10. The validation result of the effect of image texture. (a) is the input image and target color combinations, (b) is the result without adding textures, and (c) is the result generated by adding textures.

D. COMPARISON WITH STATE-OF-THE-ART METHODS

We compare our method with Wang et al.'s method [9] which can enhance an image with a given color combinations as shown in Figure 11. The source image in Figure 11 is textureless and we ignore the transcendent texture color constraints on color corresponding. Wang et al.'s method [9] may introduce a nonoptimal color correspondence and causes a further color blur (the large grey green background areas are the mixed result of the last two colors in the predefined theme), which is mainly due to the incorrect texture information in these cartoon styles. The closest color replacement principle we employ can avoid such a problem. Figure 11 also shows the comparison of our method with a recoloring method based on color palette [8]. Chang et al.'s method [8] is to re-color the input image with a given color combinations. The method presents a phenomenon of fusion with the original color. The color of the ship in Chang et al.'s result in Figure 11 is obtained by fusing the first color and background orange in the color template. This method may lead to incomplete color re-coloring. In contrast, our method can accurately express the color of the template.

Figure 12 shows the comparison between an emotion adjustment method proposed by Wang *et al.* [12] and our method. Wang et al. used color models with a fixed CN (5-color) to transfer images. In this paper, we dynamically determine the CN as well as HN in target color models. Figures 12(b) and 12(c) use a fixed template for color transfer. The input of Figures 12(b) and 12(c) contains fewer colors

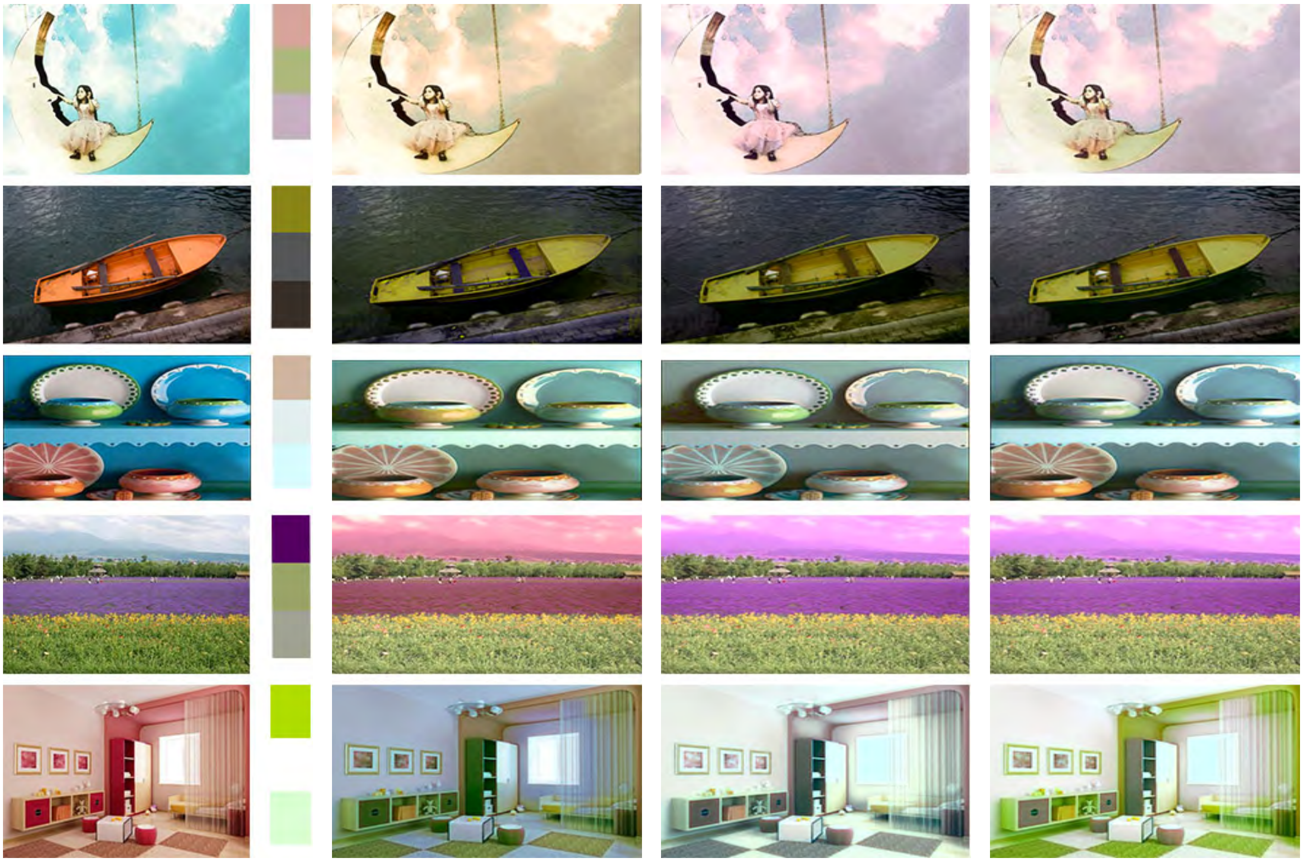


FIGURE 11. More comparison results. From left to right: the input image and target color combination, the result generated by Wang et al.'s method [9], the result generated by Chang et al.'s method [8], and the result generated by our method.

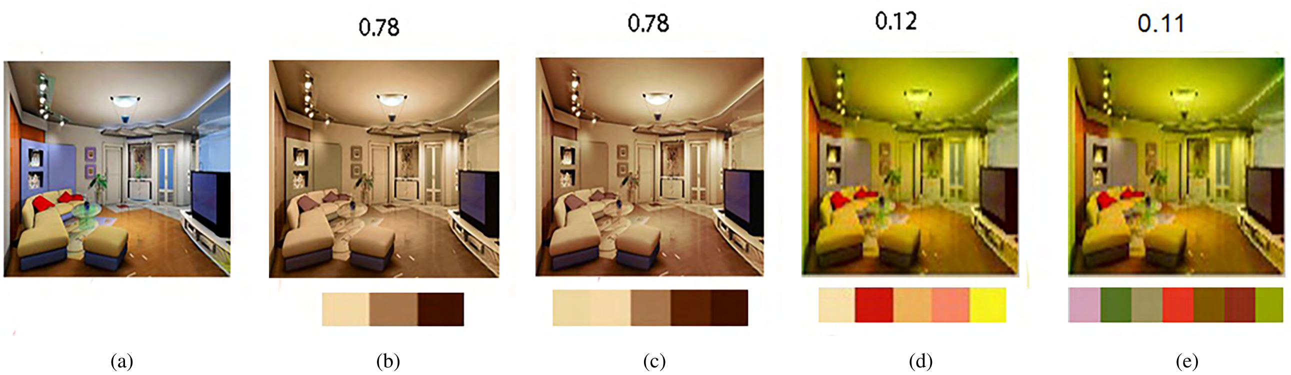


FIGURE 12. Comparison of emotional color transfer using color combinations with different color numbers. (a) is the original images, (b) and (c) are Wang et al.'s results [12] using a 3-color color model and a 5-color color model, (d) and (e) are the results generated by our method using a 5-color color model (the same as the Wang et al.'s method [12]) and a 7-color color model.

and the two results look the same. Figures 12(d) and 12(e) are generated by dynamically determining the number of colors and the number of hue. Our method classifies the Figure 12(a) as emotion of "Sensual". The color transfer results of Figures 12(d) and 12(e) are more in line with the emotion of "Sensual". Furthermore, we calculate the emotion distance of the third result and fourth result in Figure 12 using our evaluation method in Section VI. The results are 0.78, 0.78, 0.12 and 0.11, respectively. Overall, it can be concluded that our method can get more accurate emotion than [12]. Besides, 3-color and 5-color color models are not suitable for image which contains too many colors. And in our method, we adopt a 7-color color model to avoid those problems, as shown in the rightmost image in Figure 12.

Figure 13 presents the comparison between our method and an emotional color transfer with reference images [13].

FIGURE 13. Comparison with the method of [13]. (a) is the reference image, (b) is the source image, (c) is the result generated by our method, and (d) is the result generated by Yang et al.'s method [13].

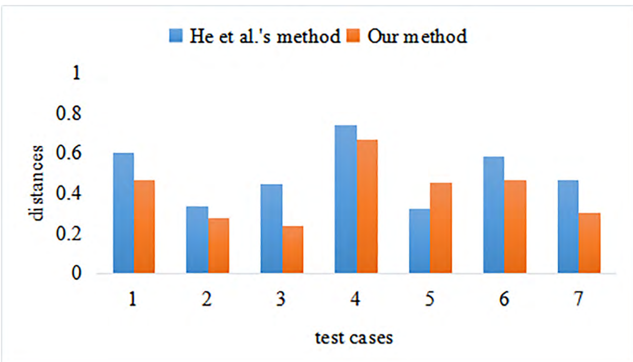


FIGURE 14. Comparison of emotion distance between input emotion words and result images. The horizontal axis is the seven test cases and vertical axis is the emotion distance. The low distance indicates that the emotion of the result image is closer to the emotion word. Note that our method has six test cases with distances lower than those of He et al.'s method, which shows the advantages of our method.

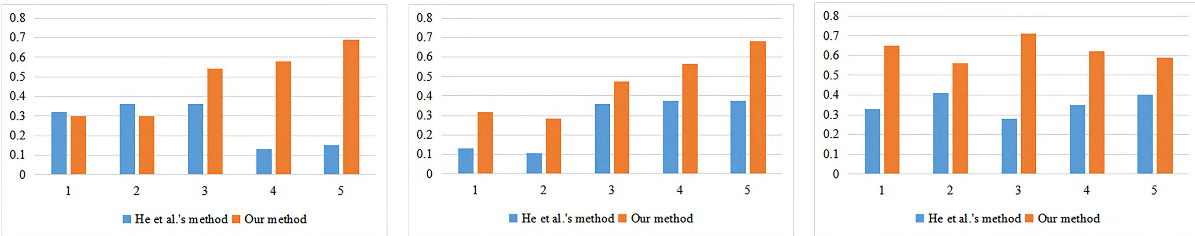
In Figure 13(d), the purple color does not appear in the reference image and the red color missed. Moreover, we calculate the distances between the two results and reference image using the method in Section VI. The results are 0.16, and 0.78 which indicate that the emotion of our result is more consistent to that of the reference image.

We compare our results with He et al.'s method [14] by calculating distances between the results and input emotion words using the method in Section VI. We randomly select 7 test cases and get the distance values as shown in Figure 14. From Figure 14, we can see that the results of our methods are closer to input words in the most test cases.

E. USER STUDY

To further evaluate our approach, we conducted a user study. We invited 16 participants (4 females and 12 males) with ages ranging from 20 to 30. They are university students, and all of them have normal vision. We chose 25 test cases, including both indoor and outdoor scenes. Two experiment comparison cases were shown in Figure 15 (''romantic'' and ''sweet''). We used two methods (our method and He et al.'s method [14]) to edit these images into 5 emotions (''romantic'', ''sweet'', ''fresh'', ''vigorous'', ''traditional''). For every emotion, a paired T-test was conducted to evaluate the difference between the resulting image of our method and that of He et al.'s method. The T-test value less than 0.05 indicates a significant difference between the two methods. Participants were shown a source image, the emotion words and its explanation, the results using our method and He et al.'s method

FIGURE 15. Comparison with He et al.'s method [14]. From left to right in each group: source image, our result, and He et al.'s result. Note that there is a large area of color blocks in He et al.'s result, e.g., there is a clear blue block in He et al.'s result in (a). In contrast, there is no large area of color blocks in our result which appears more natural. (a) Romantic. (b) Sweet.



(a) (b) (c)

FIGURE 16. Statistics of the user study. (a) image color over natural score statistical results; (b) image expression target emotional score statistical results; (c) the hit rate of each emotion.

in a random order. Participants rated their confidence on the emotion in each image according to their first impression. For each test case, participants were asked to rate the two images by two criteria: (1) the naturalness of the image color; and (2) the accuracy of the image to express emotions.

In other words, if a participants feels that the result image of our method looks natural and also matches the emotion, he/she should give a high confidence score. Confidence was quantified into 7 discrete levels ranging from 0 to 6. Thus, we collected two sets of sample confidence values for the adjusted images by our method and by He et al.'s method. Then, we performed a paired T-test on these samples to evaluate the difference between our method and He et al.'s method.

$$H_0 : \mu_a \geq \mu_{b,}$$
$$H_1 : \mu_a < \mu_{b,} \tag{11}$$

where μ_a represents the mean score of the result image of He et al.'s method, while μ_b represents the mean score of the result image of our method. Hypothesis H_0 means that the score of He et al.'s method is more consistent with the image emotion, which means that our method cannot well transfer the image's emotion.

Then, we analyzed the statistics on the collected data. We observed that the results by our method were better than He et al.'s method.

1. Figure 16(a) shows the score of answers to Question 1. We calculated the overall mean score. The score of He et al.'s method is 2.56. And the score of our method is 3.44. The higher score shows that the results of our method are more natural.

2. Figure 16(b) shows the score of answers to Question 2. We calculated the overall mean score. The score of He et al.'s method is 3.28. And the score of our method is 3.43. Our method can express emotion better than He et al.'s method.

3. Figure 16(c) shows the hit rate of each emotion. We can see from the result that the hit rate of our method is higher than He et al.'s method for each emotion.

4. Table 3 shows all five paired T-test results. Note that all two tailed P values are less than 0.05, and all T values are negative, indicating that H_0 is rejected with statistical significance and H_1 is accepted. This shows that there is a significant difference between our method and He et al.'s method. This concludes that our method has significantly enhanced the desired color emotion.

TABLE 3. Paired T-test results ($\alpha = 0.05$).

No.	Emotion	T	P(two-tail)	Confidence Interval
1	romantic	-7.425	.000000	[-11.72648,-6.64852]
2	sweet	-5.898	.000002	[-10.43352,-5.06648]
3	fresh	-3.485	.001538	[-6.77641,-1.72359]
4	vigorous	-3.518	.002005	[-8.64871,-2.22629]
5	traditional	-4.245	.000244	[-8.51643,-2.98357]

We also analyzed some statistics on the collected data: 73.25% of participants chose the results generated by our method and 79% of participants considered our results are more natural.

However, the reasons behind the superior results are understandable. First, we automatically select the appropriate color model based on the hue of the image. Second, we build a color theme database. This can effectively associate the word with the appropriate candidate color theme.

VIII. CONCLUSION AND FUTURE WORK

We have proposed a texture-aware emotional color transfer framework, which can change an image's color to meet a desired emotion calculated from a reference image or an emotion word. A new emotion calculation model was proposed for obtaining a more accurate target emotion from a reference image. We designed a novel strategy to select the most suitable color models from the predefined databases. Finally, a new color transfer algorithm was proposed, which can guarantee the color gradient and the naturalness of the result. The experimental results and comparisons showed the advantages of our method. Our paper provides a useful tool for emotionally image editing, which facilitate the non-professional users to express their creative thoughts. Our system has potential applications in many fields such as digital special effects, cartoon production, computer games, etc.

Although our method can handle most of the cases successfully, it also has some limitations. First, based on the existing theories, we have not found a satisfactory method to model the shape's influence on image's emotion. Second, the amount of 7-colors model is small, which limits the accuracy of the resulting emotions. In the future, we will optimize the performance for the above problems. We will introduce more color-emotion models especially in 7-colors model to get more accuracy emotions of the results and explore new color correspondence method to produce more natural results.

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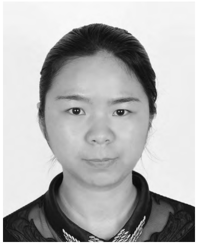

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