Color Conceptualization

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ABSTRACT

In this paper, we propose a method to manipulate colors of an image. Based on a library of natural color images, our system evolves several prototypes of color distribution of the library, which we call "*color concepts*". By applying these color concepts on an input image, a user can easily change the mood of image colors in a global manner. Our results of photographs and paintings indicate that this method is capable of high-quality color manipulations.

Categories and Subject Descriptors

I.4.8 [**IMAGE PROCESSING AND COMPUTER VISION**]: Scene Analysis - Color

General Terms

Algorithms, Design, Experimentation

Keywords

Color Concept, Color Transfer, Scene Analysis

"Autumn" conceptualized image "Forest" conceptualized image

The input images are applied to "spring" and "autumn" concepts respectively. The left part of each image displays the original input, while the right part is the output of color conceptualization.

Figure 1: Examples of color conceptualization.

1. INTRODUCTION

The organization of colors is an aesthetic issue. In artworks such as photographs and paintings, the composition of colors can convey highly abstract meanings – which are hard to be quantified with pixel-wise analysis. In order to edit colors in a more efficient way, a series of techniques known as *color transfer* have been developed [4, 7]. In [7], Reinhard replaced the first and second order statistics of the input image with that of the reference image. Then, the color composition of the input image can be altered. This technique provides alternative manipulation approaches to colors. The bottleneck of image-based color transfer is the selection of reference images: a user have to manually select a reference image that contains desired color compositions but does not have undesired colors. More recently, Daniel Cohen-Or and et. al. [2], based on empirical harmony theories of colors, proposed a method for unsupervised color enhancement. By fitting the color histogram of a harmonic scheme, incongruent colors can be replaced by colors that satisfy established harmonic rules. However, color harmonization is a full automatic approach. A user cannot use it to edit colors based on his/her subjective ideas.

In order to modulate the color composition of an image to achieve particular purposes of users, we propose a novel framework to quantify the subjective, artistic "moods" of colors, and use it as the tool for image modification. The paper is organized as follows: in section 2, we discuss the possible origin of human impressions on "typical prototypes" of color distributions, which is called *color concepts*, and present a clustering approach to extract these color concepts from the input image library; in section 3, we offer an image coloring method by propagating a desired concept to the input; in section 4, we demonstrate manual image recoloring and automatic color optimization results based on the color conceptualization theory; finally in section 5, future work and limitations of the method are addressed.

2. COLOR CONCEPTUALIZATION

A school of researches [1, 5, 9] aims at explaining the formation of color naming system from an evolutionary perspective. These studies believe that verbal terms describing colors are shaped by the clustering of natural color distributions. In addition, computer simulations [1] also corroborate this idea. According to these theories, we propose a clustering model to generate prototypes of color distributions such as "warm" and "cold", from an input image library.

In section 2.2, we introduce the hue wheel representation of image color distributions, and use it in section 2.2 to cluster images into different categories. For each category, we

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extract its particular *color concepts*, which corresponds to the representative color mood of images within the category.

2.1 Hue wheel representation

We use hue wheel to represent the holistic color distribution of an image. First, the image is converted into the HSV color space. Since low saturation or low lightness degrades the perception of colors significantly, we define the hue wheel $H(\theta)$ as following:

$$H_I(\theta) = \sum_{i(H)=\theta} i(S) \cdot i(V) \qquad i \in I, \tag{1}$$

where θ is the hue value; i is the HSV-valued pixel in the image; and I is the input image. Similarly, the hue wheel of a set of images can also be obtained by calculating the weighted hue distribution over all images.

Given the input image and a set of images belonging to one cluster, their distance must be measured. A "neighboring" input image will be incorporated into the cluster, while a "distant" input will be considered as a new cluster. In this paper, we use *KL divergence* to measure the distance of color compositions. Given the hue wheels of the input image $H_i(\theta)$ and that of an image category $H_C(\theta)$, the distance $D(i \parallel C)$ is defined as:

$$D(i \parallel C) = \sum_{\theta} H_i(\theta) \log \frac{H_i(\theta)}{H_C(\theta)}. \tag{2}$$

Note that the KL divergence is not symmetric. In our experiments, the distance $D(i \parallel C)$ is calculated from a given cluster to an input image.

2.2 Clustering hue wheels

Experienced with color scenes, a human observer refines his color representation by epitomizing colors with language [1]. Terms related to color impressions such as "coastal blue" distinguish particular color moods from random color distributions. From a statistical perspective, we simulate the evolution of the conceptualization process by clustering the hue wheels of the image database. As shown in figure 2, images sharing similar color composition are "conceptualized" into the same category.

We adopt the CVCL database [6] as the library for color conceptualization. In this database, 2688 images are manually classified into 8 themes based on their semantic content, such as "coast", "forest", and "open country". The clustering is performed on each theme separately.

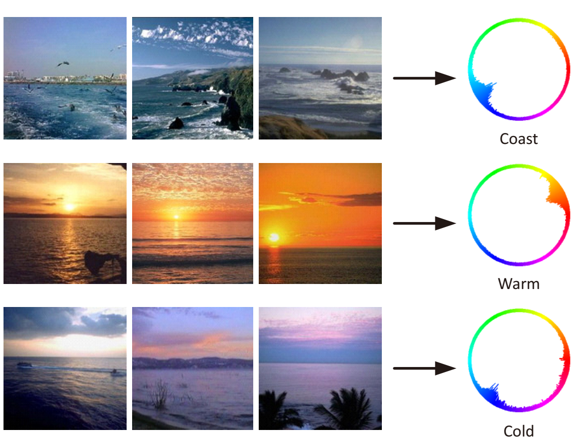

Figure 2: Conceptualization results of the coastal pictures

First, we randomly choose an image as an independent cluster; this cluster assimilate its "neighboring" images until all other images have distances greater than the threshold σ (in our experiments, $\sigma = 1.5$). Then, a new cluster is generated from the rest of the image set, iteratively. C denotes the entire image set, C_k denotes the k^{th} cluster ($k > 0$), and C_0 denotes the set of images that is not yet categorized. $C = \bigcup C_k$. p_i denotes the i^{th} image. The clustering process is described in **Algorithm 1**.

Algorithm 1: Clustering hue wheels

1. If $C_0 \neq \emptyset$, initiate a new cluster C_k by randomly picking a new image p_k from C_0.
2. Find the neighboring image p_m by:
$$p_m = \arg \min_{p_i \in C_0} D(p_i \parallel C_k).$$
3. If $D(p_m \parallel c_k) \leq \sigma$, exclude p_m from C_0; include p_m into C_k; and goto step-2. Otherwise goto step-1.

After clustering, we ignore categories having less than 10 images, because the least populated categories are not expected to address the general trends of color compositions. Finally, we label each category with a subjective description that addresses its primary color impression.

3. CONCEPT-BASED COLORING

A peak in a hue wheel represents a population of similar colors. There could be either a single peak ("coast" and "warm" in figure 2), or multiple peaks ("cold" in figure 2) in a hue wheel. In order to provide greater latitudes to the color edition, we further decouple a hue wheel into regional color peaks, and use it as the atomic unit in the color editing process.

In section 3.1, the spatial continuity of colors is discussed. An algorithm is proposed to optimize the peak detection. In section 3.2, we use a peak mapping method to propagate a color concept to the input image.

3.1 spatial continuity of colors

In our color manipulations, we express the desired color mood by mapping the peaks of the input hue wheel to that of a desired concept. During this process, the spatial information of colors is discarded. However, shifting a hue wheel often lead to spatial discontinuities, such as (b) in figure 3.

The origin of the discontinuity problem is the pixels at the cutting point [2]. Perceptible discontinuities occur when some pixles of a spatial continuous region are recolored by peak shifting, while the rest are not. In order to avoid this problem, we must cut the hue peaks from hue wheel "gaps". A "gap" in hue wheel suggests the absence of pixels with corresponding colors in the image. Therefore, separating the hue wheel from these "gaps" will not split one continuous region into two or more colors.

Algorithm 2 presents our method to cut a peak Λ_i. Given a local maximum $H(\theta_i)$, the shape of a peak is damp-

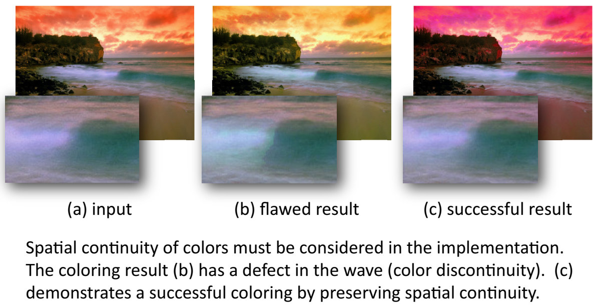

Figure 3: An example of spatial continuity of colors.

ened by a Gaussian function $G_{\mu,\sigma}(\theta)$, where μ is the mean, and σ is the variance of $G_{\mu,\sigma}(\theta)$. This method preserves the shape of a peak in the center part, and at the same time guarantees a local minimum to cut – the number of pixels separated by a cut is always small enough to avoid region discontinuities.

Algorithm 2

1. Fit the peak $H(\theta_i)$ with a Gaussian function:
$$(\theta_i, \sigma_i) = \arg\min_{\theta,\sigma} \sum_{\theta} |H(\theta) - G_{\theta,\sigma}(\theta)|$$
2. Initiate the left cut position: $\theta_L = \theta_i - 2.5\sigma_i$.
3. Extend θ_L to the left , until $H(\theta_L) = 0$, or $H'(\theta_L) = 0$.
4. Apply step 4 and step 5 to the right cut position θ_R.
5. $\Lambda_i = (1-\omega) \cdot H(\theta) + \omega \cdot G_{\theta_i,\sigma_i}(\theta)$, where ω yields :
$$\omega = \frac{|\theta - \theta_i|}{\max\{\theta_i - \theta_L, \theta_R - \theta_i\}}$$
6. Update the hue wheel by: $H(\theta_i) = 0$, $\theta_i \in [\theta_L, \theta_R]$

3.2 Propagating color concepts to images

Given the hue peaks of a concept and that of an input image. We can propagate the color concepts to the image by modifying the image hue peaks to the corresponding shapes of a concept. The pairing of peaks can either follow manual instructions or select the nearest peaks automatically. Both results are provided in section 4.

Assume we are given an image hue peak Λ_i and a concept hue peak Λ_C, we can "propagate" the color concept by matching hue value in Λ_i with a corresponding value in Λ_C. Specifically, we normalize a hue peak by the quantile function $R(\theta, \Lambda)$:

$$R(\theta, \Lambda) = \frac{\int_{t=\theta_L}^{\theta} \Lambda(t)dt}{\int_{t=\theta_L}^{\theta_R} \Lambda(t)dt}, \tag{3}$$

then, we use **Algorithm 3** to perform the concept propagation.

Algorithm 3

1. Calculate $R(\theta_i, \Lambda_i)$.
2. Find $\hat{\theta_C}$ that satisfies $R(\theta_i, \Lambda_i) = R(\theta_C, \Lambda_C)$. Since $R(\theta, \Lambda)$ is a strictly ascending function. the solution $\hat{\theta_C}$ is unique.
3. Assign $\theta_i = \hat{\theta_C}$.

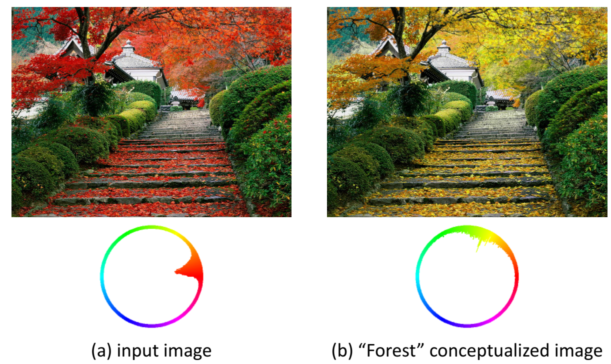

Figure 4: An example of propagating a color concept.

4. RESULTS AND APPLICATIONS

In this section, we demonstrate a series of results by manual/automatic color manipulation of images. In comparison with existing color transfer techniques, the predominant advantage of our method is the utilization of color concepts rather than particular color values or reference images. As the manual color editing examples indicate (shown in figure 5), our method is capable of conveying the color mood of an image.

In addition to the manual color edition, color conceptualization is also capable of automatic color enhancement. Given an input image, our system first compares the image hue wheel with existed concepts, and then apply the most similar cluster to the image. The similarity in this process is based on KL divergence. The automatic color enhancement is especially useful in correcting hues of an artwork - since the selection of colors during the painting process is an empirical estimation, some deviations are expected. The color conceptualization technique can correct the holistic hue of the image with the natural image data as the reference. As shown in figure 6, during the enhancement process artistic elements such as strokes or relative color proportions are preserved.

5. DISCUSSIONS

In this paper, we have proposed the color conceptualization method to modify the colors of an image. Different from previous techniques, our method compute the statistics of color compositions from an image library. Therefore, this method is free from empirical parameters or complicated manual tuning processes. Finally, we demonstrate applications of high-quality image color manipulations using color conceptualization.

The clustered color concepts represent the expectations of

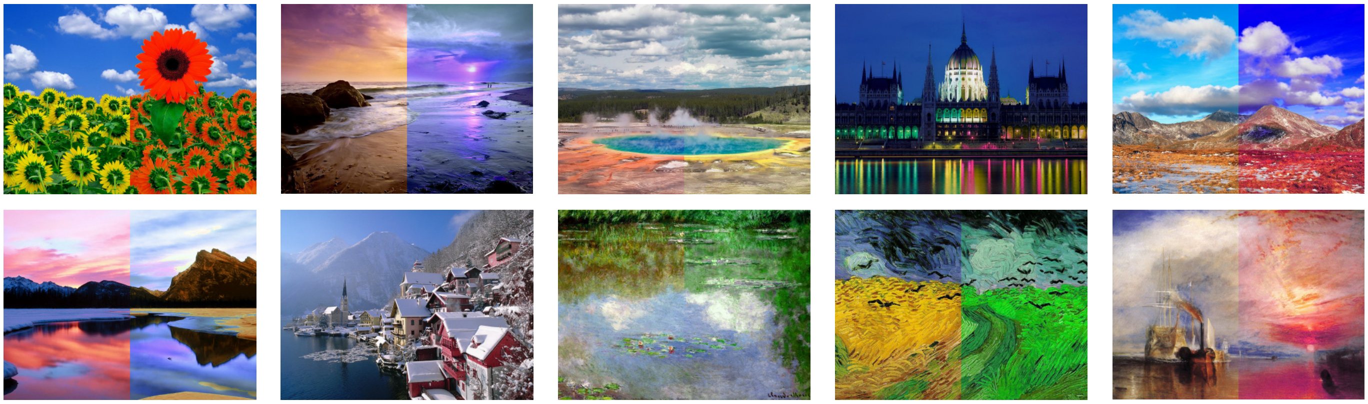

Figure 5: Examples of concept-based color edition (left input, right output).

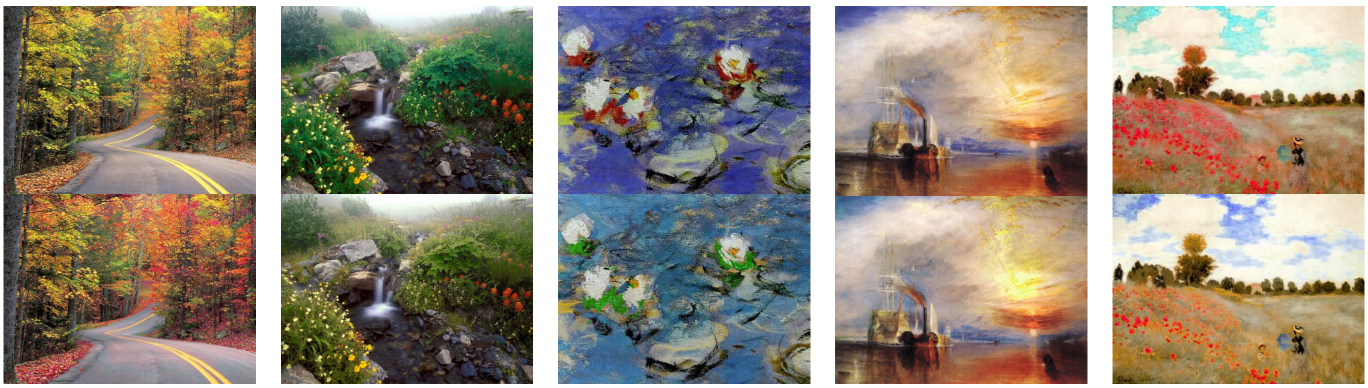

Figure 6: Examples of automatic color enhancement (top input, bottom output).

the distributions of certain semantic themes. However, what does color concepts imply, with respect to the subjective impressions of human? This question has been addressed by artists and philosophers who believe “average is optimal”. Moreover, according to the study of natural image statistics and neuroscience [3, 8], researches propose that our visual system is best tuned to the average input of the environment. It is suggestive that the color conceptualization will bring harmony to a human observer.

Without direct manipulation of pixels, the color conceptualization simplifies the operation of colors in an image. At the same time, this method loses pixel-specific control over spatial domain. Therefore, the performance of our method is more remarkable to spatially complex images, such as foliage, than in spatial uniform regions – which is simpler to be modified by a spatial method.

6. ACKNOWLEDGEMENTS

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