COLOR STYLE TRANSFER BY CONSTRAINT LOCALLY LINEAR EMBEDDING

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ABSTRACT

This paper presents a new semi-automatic method for color style transfer between images, which enhances the artistic expression of a image while preserving the content. Our method consists of three steps. (1) We first parse an input image into several semantic objects according to different material properties using interactive algorithms. (2) We search for a proper reference image from library using the semantic information. (3) The dominant colors of the input image and reference image are computed by clustering, and then we propose a constrainted locally linear embedding (CLLE) algorithm to perform color style transfer on the input image. In the experiments, we apply the proposed method to several photos to produce expressive results.

1. INTRODUCTION

Color style transfer is one of the most common tasks in image processing. By altering the color, we can receive new image understanding from the same scenes, such as converting grass from yellow to green to suggest the change of season. This paper presents a novel color transfer framework for converting the input image color to the reference image color style. A representative example by our framework is shown in Fig.1.

(a) (b) (c)

Fig. 1. Exemplar illustration of image color transfer using proposed algorithm. Image (a) is the source image, (b) is the reference image, and (c) is the color transferred image.

Related work. In the literature, early color transfer techniques are mainly statistics-based algorithm [1] [2]. Reinhard [1] presented a global Gaussian distribution to impose one image color characteristics on another. Pitié et al. [2] proposed a global color transfer method to estimate a continuous transformation that maps one N-dimensional distribution to another. A major disadvantage of this color histogram based approaches is that they can not preserve the local information. Rather than transfer the color from one image to another globally, Tai et al. [3] and Huang et al. [4] presented local-based algorithm for color transfer. Huang et al. [4] employed a landmark-based sparse color representations for color transfer, which characterizes a color image by an intensity image and a small number of color pixels. Tai et al. [3] presented a Local color transfer method by segmenting image with soft region boundaries for seamless color transfer and compositing. Another type work is to categorize pixel colors into basic color categories represented by Chang et al. [5], which first divides the color space into the eleven basic color categories, and then the algorithm segments the input photograph and reference painting using those categories.

A recent work which motivated this paper is a coloring the monochrome image by linear neighborhood embedding algorithm [6] which employed a modified LLE algorithm. Locally linear embedding (LLE) [7] characterizes the local geometry of a high dimensional manifold by linear coefficients that reconstruct each data point from its neighbors. The local geometry in a high dimensional space is then transmitted to a new(or low dimensional) space by (global) embedding.

Fig. 2. Several images selected from the reference image library.

The proposed algorithm in this paper has three advantages. The first advantage is that we study a novel color transfer algorithm named color transfer by constrainted locally linear embedding in RGB color space, which can characterize the local color information. Another one is that the reference image which have the same semantic labels with the input im-

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age is searched from the reference image library rather than inputted by users.The last advantage is that only in this way should we use typical colors as little as possible to change the color style instead of the statistic approach.

Overview. The proposed method consists of three parts: **Interactive Image Labeling and Reference Image Searching**, **Color Clustering** and **CLLE Color Transferring**.

In the first part, we employ a multiway cut algorithm to segment the input image into independent regions and then classify the segmented regions using texton boosting algorithm (see Fig.4). In our system we build a reference image library, in which 1000 images with beautiful colors are collected by hand. Employing a semantic label-matching approach we can find a reference image from the image library (in Sec.2).

In the second part, we character the local colors of the reference image and input image using the ISODATA approach (in Sec.3).

Finally, our proposed constrainted local linear embedding (named CLLE) algorithm run for the color transfer (in Sec.4).

2. INTERACTIVE IMAGE LABELING AND REFERENCE IMAGE SEARCHING

The goal of image labeling is to parse the source image into a set of semantic regions (i.e., region with semantic labels). Automatic image segmentation is an open problem in computer vision which requires modeling the problem based on domain prior knowledge. As alternative image segmentation, interactive image segmentation is a slightly easier approach which received a lot of attention over the years. In this paper we develop a software interface to obtain interactive instructions from users for reliable segmentation results using a multiway cut algorithm [8].

Let **I** be an input color image. Our goal is to segment the image into K disjoint semantic regions R_i for $i = 1, 2, ..., K$. These semantic regions correspond to different objects with semantic labels, such as the sky, the grass,the house et al. Fig.4 shows a set of typical segmented and labeled regions for a source image.

(a) Sky (b) Source Image (c) Grassland

Fig. 4. The input image is segmented into two regions simultaneously by placing user stroke with different colors; then these regions are classified into two categories

To segment the image **I**, a user simply draws scribbles in each region R_i using different colors, as shown in Fig.4. Then we adopt an α-expansion algorithm [8] to segment the image simultaneously into K regions.

$$\Lambda = \Lambda_1 \cup \Lambda_2 \cup \cdots \Lambda_K$$

in which Λ is the domain of the whole image lattice, Λ_i is the domain of ith region, $\Lambda_i \cup \Lambda_j = \phi$ for all $i \neq j$;

After the segmentation, each region R_i is further assigned a semantic label l_i corresponding to twelve material categories. A recently proposed method, namely texton boosting[9], is employed for image region classification. In fact, as the regions are already well segmented, the classification is easier and more accurate.

After image labeling, we will choose a reference image from reference image library according to the semantic label information of the input image. That is to say a pair of input image and reference image should have the same semantic regions, further more each region will cluster a dominant color for CLLE in Sec.3. For example, a pair of images in Fig.1 will be firstly segmentated into two semantic regions: the sky and the grass, and each region will cluster a dominant color.

3. COLOR CLUSTERING

Unlike the global color transfer algorithm [2], we will character the local color of the input image and reference image with an unsupervised color clustering approach.

The two most frequently used clustering algorithms are the K-mean and the ISODATA algorithm. We have tried these two approaches to cluster the main colors for the input and reference image. The experimental results show that K-Mean is inferior to ISODATA for the color clustering in that the ISODATA algorithm using the random starting point allows for different number of clusters while the k-means assumes that the number of clusters is known as a priori.

To speed up the ISODATA algorithm, we borrow an approximate efficient approach [10], which can achieve better running time by storing the points in a kd-tree and through a modification of the way.

Fig. 5 shows an illustration of image color clustering and color transfer by CLLE. Source image Fig.5(a) and reference image Fig.5(d) are a pair image for color transfer. Each region will cluster a dominant color Fig.5(b) and (e) are the correspondence color distribution in RGB space. For each semantic region, we run the color clustering algorithm [10] and obtain the main color which corresponding to the cluster with most data. The mainly color are showed with rectangle and circle in Fig.5(c) and (f).

4. COLOR TRANSFER BY CONSTRAINTED LOCALLY LINEAR EMBEDDING

For a given source image $\mathcal{S}$ and reference image $\mathcal{R}$, we directly alter the source image color to reference image color in a RGB color space $\mathbb{R}^3$ ($\mathcal{S} \subset \mathbb{R}^3$, $\mathcal{R} \subset \mathbb{R}^3$). Before color transfer by CLLE, the main colors of image $\mathcal{S}$ and $\mathcal{R}$ are extracted, and then we run the CLLE algorithm to return a color-transferred image $\mathcal{O}$. The major six procedures are shown as follows.

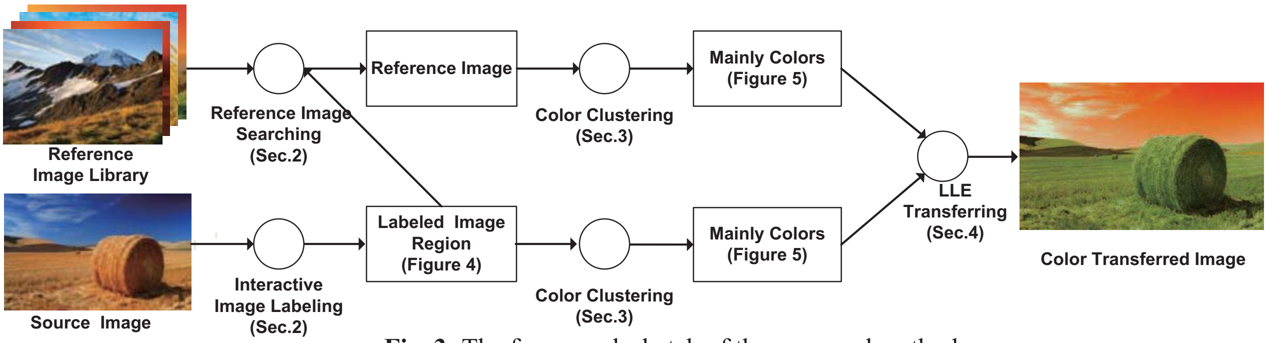

Fig. 3. The framework sketch of the proposed method.

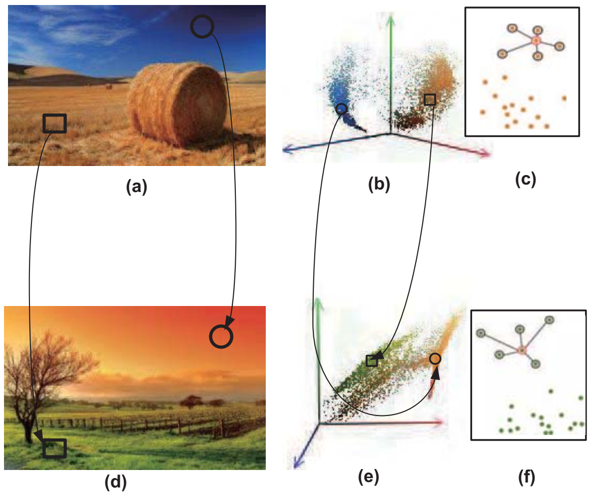

Fig. 5. The illustration of image color clustering and color transfer by CLLE.

- **Step 1**: Obtain all colors $X1$ from Source Image $\mathcal{S}$, $R1$ from Reference Image $\mathcal{R}$.

$$\begin{aligned} X1 &= \{x_1, x_2, \cdots, x_n\}, x_i \in \mathbb{R}^3 \\ R1 &= \{r_1, r_2, \cdots, r_m\}, r_i \in \mathbb{R}^3 \end{aligned}$$

  If two pixels in the image have the same color only one color will retain in $X1$ or $R1$.

- **Step 2**: After interactive image labeling (in Sec.2), the dominant color sets C_r, C_x for each semantic region will be clustered using a fast ISODATA clustering algorithm(in Sec.3) for image $\mathcal{R}$ and $\mathcal{S}$.

$$\begin{aligned} C_x &= \{x^{(1)}, x^{(2)}, \cdots, x^{(K)}\} \\ C_r &= \{r^{(1)}, r^{(2)}, \cdots, r^{(K)}\} \\ X &= X1 \cup C_x, |X| = N + K \end{aligned}$$

  where the dominant color sets C_r, C_x are the hard constraint for local linear embedding.

- **Step 3**: Find k Nearest Neighbors for each element in X using a approximate nearest neighbour(ANN) searching algorithm [11].

- **Step 4**: Solve for local reconstruction weights W as done in LLE.

$$\begin{aligned} W^* &= \arg\min \varepsilon(W) \\ &= \arg\min \sum_i |x_i - \sum_j W_{ij} x_j| \end{aligned} \quad (1)$$

  subject to: $\sum_j W_{ij} = 1$;

  where the weight W_{ij} summize the contribution of color x_j to x_i reconstruction.

- **Step 5**: Compute embedded colors Y using reconstruction weights

$$Y^* = \arg\min \sum_i |y_i - \sum_j W_{ij} y_j| \quad (2)$$

  subject to: $y_{N+1} = r^{(1)}, \cdots, y_{N+K} = r^{(K)}$;

- **Step 6**:Compute color-transferred image $\mathcal{O}$ with the color mappings from $\{X_i\}$ to $\{Y_i\}$.

5. EXPERIMENTS

Fig. 6 shows some experimental results using our color transfer method. The first two column images are the source image and reference image, and the last two column images are the results of our proposed approach and Reinhard et al.[1] method. All the experiments are done in Matlab on PC with Dual-Core 2.93GHz CPU. Results show that a color clustering phase takes around $1 \sim 2$ minutes, while LLE transfer phase takes around $3 \sim 5$ minutes.

Furthermore, we compare our approach with the method of Reinhard et al[1]. The results of the compared images demonstrate a better color transfer effect on both background scenes and foreground objects. From Fig.6(c) and Fig.6(d), we can see that the color transfer results (Fig.6(d)) produced by Reinhard et al[1] look unnatural while our approach generates more natural and less artifact results(Fig.6(c)). Moreover, the results are visually satisfied and closer to the expected result according to the reference images.

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

Fig. 6. Experimental results. (Please view in high 400% resolution in Acrobat reader)

6. REFERENCES

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