Homogenous Color Transfer Using Texture Retrieval and Matching

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Abstract. Color transfer is a simple but effective technique of realistic rendering. Most methods of color transfer select the source image manually, which makes an inconsistent transformation in semantic areas. We propose a novel approach of homogenous color transfer by using texture retrieval and matching. Several images are found out from a database using the texture features of a target image, then the image with the highest texture similarity is set as the source image. With a simple interaction of brush stroke in the target image, the texture features of the covered pixels are used to extract a homogenous region in the source image and match between such regions. Afterwards, an adaptive color transfer scheme is applied in the matched regions. Owing to the texture retrieval and matching, this method produces a consistent visual effect results. We demonstrate experiments in image colorization, style conversion and exposure adjustment to verify the characteristics.

Keywords: Color transfer · Texture retrieval · Regions matching

1 Introduction

Color transfer is a research hotspot of image processing, which aims at changing the color style of a target image from a source image. It is widely used in many applications, such as movie making and artistic-designing. Most existing methods tried to avoid manual interaction so that they could be much more efficient and convenient than specialized tools such as Photoshop etc. Figure 1 demonstrates an example of color transfer which shows that the transferred result keeps both the content of the target image and the color style of the source image.

In the last decades, color transfer techniques have attracted increasing attention. Reinhard et al. [1] proposed a color transfer method by estimating the mean value and deviation of each channel, which is the basis of most color transfer methods based on statistical features. Pitie and Kokaram [2] proposed the best linear color transfer method, which used Monge-Kantorovicth theory of mass

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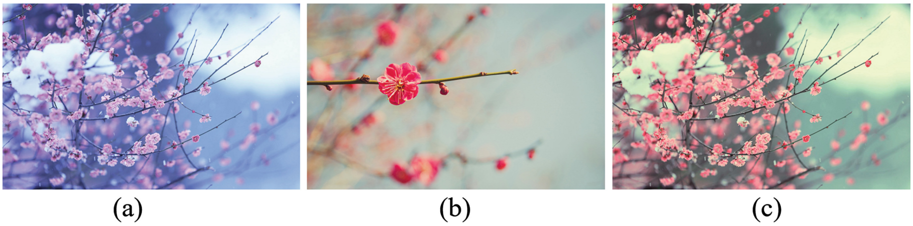

Fig. 1. Example of color transfer. (a) Target image. (b) Source image. (c) Transfer result.

transportation to minimize the amount of color changes. Considering the spatial variation of color distribution, some methods using local features of images are presented. Tai et al. [3] optimized local color matching via probabilistic segmentation and apply an Expectation-Maximization scheme to infer the natural connectivity among pixels. Pouli et al. [4] proposed a novel histogram reshaping method that manipulated histograms at different scales and allows coarse and fine features to be considered separately. HaCohen et al. [5] presented a method that uses Generalized PatchMatch and a coarse-to-fine scheme to enhance the correspondence regions between two images with shared contents. Kagarlitsky et al. [6] proposed a method that performs color mapping between pairs of images under various acquisition conditions.

The source image is chosen manually in most color transfer methods. In many cases, the corresponding regions don't have any consistency in their physical attributes, such as semantic category. Undesirable results may be produced if the source image is inappropriate. e.g. the skin of a person in the target image would turn blue if the source image is a sunshine landscape. Besides, the manual selection increases the workload and the instability of the transferred results.

In this paper, a novel approach of homogenous color transfer based on texture retrieval and matching is proposed. Texture features of a target image are used to search a source image with similar content. Then, the color style is transferred between the corresponding texture regions from the source to the target. The main contributions of this paper are as follows:

- We propose a novel approach of color transfer using texture retrieval and matching. The source image is selected according to its texture similarity to the target image to ensure the rationality of the source selection.
- The corresponding regions of the source image and the target image are extracted and matched according to the features of a manual selected texture kernel. Then, the luminance and chrominance are processed respectively in the corresponding texture regions for the color transfer.
- The proposed approach is used in image colorization, style conversion and exposure adjustment to extend its applicability.

2 Our Approach

This section presents the processing procedures of the homogenous texture matched color transfer approach. First of all, a source image is selected from an image dataset according to the texture features of the target image. Then, the corresponding texture regions are extracted from the two images using the texture kernel which is estimated by drawing a simple brush stroke in the target image. Finally, the color style of the target image is transferred to the source image.

2.1 Image Retrieval Based on Texture Features

Generally speaking, geometry shape, color and texture provide most contributions to our awareness and understanding of an image. As a basic property of an image, texture reflects the content of an image, which decides its semantic category. The color transfer will be much more credible when the image contents of the source and the target belong to a same category than the others. Hence, it's better to choose the source image having a similar texture with the target.

Image retrieval is realized using texture features of the target image to determine the required source image. A variety of texture descriptors have been presented in the existing work over the past decades, such as gray level co-occurrence matrix (GLCM) [7], markov model algorithm (MRF) [8], discrete wavelet transform (DWT) [9] and local binary pattern (LBP) [10]. These typical descriptors each have their respective properties, and fit for describing a variety of different scenes.

The texture extract by GLCM gives out a good description for roughness of the texture. The LBP feature reflects the details of the image and it has the rotational and brightness invariance which is often used to classify the texture. The DWT feature reflects both the frequency domain information and the spatial information of the image, which can be used to do the multi-scale analysis. We introduce a texture descriptor with multi-features by combining GLCM, LBP and DWT. It is operated by merging the three feature vectors to be a comprehensive feature. At the beginning, the three feature vectors of a given image are extracted respectively. Setting the texture feature vector extracted by GLCM is $V_{GLCM} = [x_1, x_2, x_3, ..., x_i]$, the feature vector of the rotation invariant unified LBP model is $V_{LBP} = [y_1, y_2, x_3, ..., y_j]$ and the feature vector of DWT is $V_{DWT} = [z_1, z_2, z_3, ..., z_k]$. The merged vector is represented as $V = [x_1, x_2, ..., x_i, y_1, y_2, ..., y_j, z_1, z_2, ..., z_k] = [f_1, f_2, ..., f_N]$, thus the dimension of the vector $N = (i + j + k)$. Since the element value of the three vectors vary in the range, a Gaussian normalization is taken to limit the value range into $[0, 1]$, the Gaussian normalization is given by:

$$F_{p,q} = \frac{v_{p,q} - \mu_q}{\delta_q} \tag{1}$$

where $I_1, I_2 ... I_M$ represent the images in the dataset, $v_{p,q}$ represent the vector f_q of I_p,μ_q represent the average value of f_q in all the images. $F_{p,q}$ represent the

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

Fig. 2. Retrieved results. (a) Target image. (b), (c), (d), (e) are the retrieved results sorted by their texture similarity.

normalized result of $v_{p,q}$. In the source image retrieval, Mahalanobis distance [11] is used to estimate the texture similarity between the retrieved image and the target image. The distance of two images is defined as:

$$D = (F_s - F_t)^T S^{-1} (F_s - F_t) \tag{2}$$

where S represents the covariance matrix, F_s and F_t represent the normalized vector of the source and target image. GLCM descriptor is suitable for global texture, LBP descriptor is fit for detailed texture and DWT descriptor contains scale invariance. In order to be applied to images with different textures, the Mahalanobis distance of the three feature vectors are estimated respectively, and calculate a weighted sum. The weights of the three vectors are set to be adjustable. It is written as:

$$D(I_1, I_2) = \omega_1 D_{GLCM}(I_1, I_2) + \omega_2 D_{LBP}(I_1, I_2) + \omega_3 D_{DWT}(I_1, I_2) \tag{3}$$

where $\omega_1 + \omega_2 + \omega_3 = 1$ are weight coefficient of three descriptor.

Several images are picked out from the retrieved results according to the Mahalanobis distance as candidate source images for user preferences. Figure 2 demonstrates some examples of the retrieved results. The images in the figure are from Corel dataset and our own image library. It is shown that all of the retrieved results have a similar texture with the corresponding target image.

2.2 Texture Feature Based Region Matching

The texture features used in the image retrieval is estimated from the statistical information of the texture features within the global image. Actually, the similar textures between the target image and the retrieved image only occupy parts of the images. Extracting and matching the corresponding regions, and making

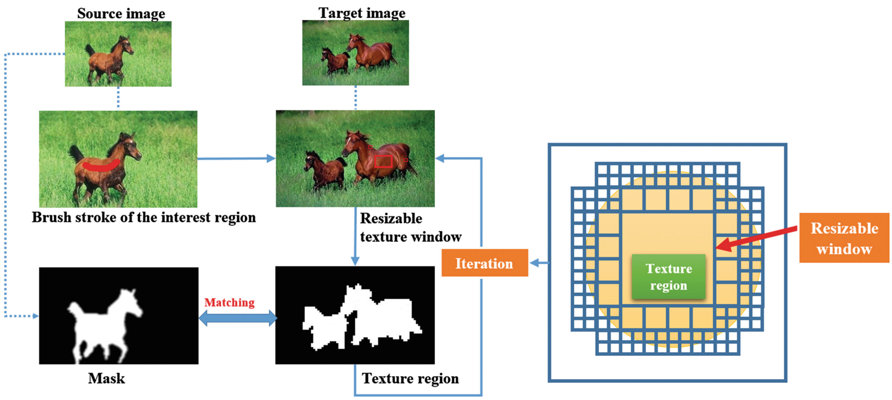

Fig. 3. Texture extraction and matched result.

the color transfer in the regions would improve the visual effect and credibility of the transferred result owing to their similar textures.

The procedure of the matching method is illustrated in Fig. 3. The first step of the method is to acquire a region of interest in the target image, which is operated by drawing a brush stroke in the image. The texture features of the covered pixels are extracted by GLCM and LBP are merged as a standard texture. Then, the retrieved source image is segmented into windows for finding the similar texture regions. The texture feature vector of each window is calculated, and compared with the extracted standard texture using Mahalanobis distance. The one having the smallest distance is selected as the core region of the textures and the features of this region is set as the texture kernel. Subsequently, the core region are expanded to enlarge the texture area. In order to make the expanded boundary as accurate as possible, a resizable texture window is used to update the boundary iteratively.

As shown in Fig. 3, large windows are used near the core area to ensure the consistency of the texture features, while the windows near the boundary are diminished to find an exact edge. The resizable windows are set as the same size with the core window starting from which the adjacent windows are set to be new members of the region if the relative texture distance is smaller than a preset threshold σ. Consequently, a rough edge is generated by the windows expansion. The size of the windows at the edge is zoomed out and the texture features of the zoomed windows are recalculated to get a more elaborate texture detail. Let μ be the texture feature of a window u within the boundary of the texture region, let l be the texture feature of a window v near u. Then the window v is merged in the texture region if $|\mu - l| < \sigma$ to refine the boundary. The process is executed iteratively to further update the region. Texture is a regional concept, which cannot be constituted by a single pixel. Thus, when the window size is too small to carry on enough texture information, the texture region is determined. In addition, to prevent the divergence of the texture area, the gradient descent is also used to restrict the boundary. Finally, the extracted texture region in the retrieved source image is matched to the mask of the target image which is extracted by user-specified segmentation mask [15].

2.3 Color Transfer Scheme

Color transfer consists of two parts: the transfer for the luminance and the transfer for the chrominance. For the first part, standard cumulative histogram method [12] is used to realize the luminance transfer, while for the chrominance transfer, Monge-Kantorovitch [2] linear color mapping method is used to transfer the color from the source image to the target in the color space LAB.

Luminance Transfer. We use the standard cumulative histogram method to transfer the luminance features. With this method, the detailed information of the image can be saved in the case of transforming the brightness histogram. The brightness distribution of the target and source images can become consistent by stretching the cumulative histogram of two images. The standard histogram of transfer function is defined as: $L_t = H^{-1}(T_l)$. H represents the normalized cumulative distribution function of irradiance, and T_l denotes the cumulative probability under the specified value in channel L within the target image. L_t means the irradiance value after migration. The result of the luminance of this target image after migration is shown in Fig. 4.

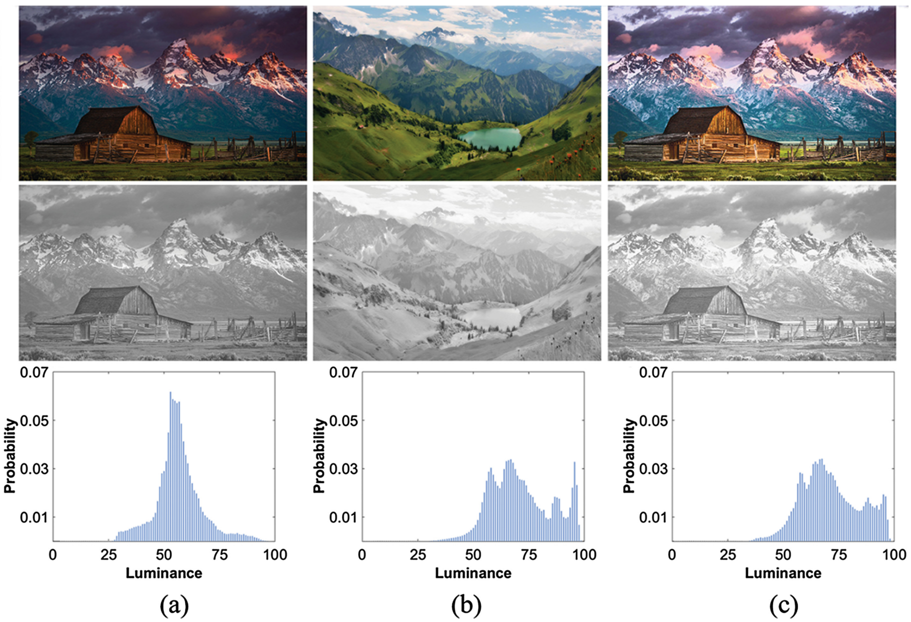

Fig. 4. Luminance cumulative histogram. (a) Target (b) Source (c) Transfer result

Fig. 5. Chrominance transfer. (a) Target image (b) Source image (c) Transfer result

Chrominance Transfer. Chrominance transfer means transferring the color information from the source image to target image. The method proposed in this paper is based on mass transfer in the field of theoretical Monte Carlo. This algorithm for color change depends on the orthogonal color space, so we need to convert the images into a three-channel decoupled Lab color space. Firstly, we use self-adaptive clustering algorithm based on K-medoids clustering method [13] to divide the image into three brightness band with the luminance information of each pixel. The Monge-Kantorovitch Linear Color Mapping is such a method that abstracts both the source image and the target image to a function, whose density distribution is continuous. With equations, a continuous T_{st} can thus be acquired so that the density distribution of the source image and the target image after transformation are similar.

The general formula description of image transform can be defined as:

$$t(u(a,b)) = T_{st}u(a,b) + t_0 \tag{4}$$

When the density function f for target image u and g for the source image v are in concordance with the Gaussian distribution, the Monte Carlo transform has the unique solution.

$$T_{st} = \sum\nolimits_t^{-1/2} (\sum\nolimits_t^{-1/2} \sum\nolimits_s \sum\nolimits_t^{-1/2})^{1/2} \sum\nolimits_t^{-1/2} \tag{5}$$

$\sum_t$ and $\sum_s$ represent the covariance matrix of the target image and the source image respectively. Figure 5 is the result of the chrominance transfer.

Weight Adjustment. In order to make the picture endowed with the characteristics of two images, variable parameters are set to adjust the weight relationship between the source and the target. As for luminance, we use ratio parameter to reset the brightness band: $L_{combine} = L_{target} * Rate \oplus L_{source}(1 - Rate)$. L_{target} represents the brightness band of the target, and L_{source} represent the brightness band of the source image. According to this formula, the luminance information of the $L_{combine}$ is re-divide and clustered. After that, the new clustering result can be used to adjust the luminance of the target image. As for chrominance, the chrominance a_t and b_t of a target image pixel are transferred to the corresponding $a_t^{'}$ and $b_t^{'}$:

$$\begin{bmatrix} a_t^{'} \\ b_t^{'} \end{bmatrix} = T_{st} \begin{bmatrix} a_t - \mu_{at} \\ b_t - \mu_{bt} \end{bmatrix} + \begin{bmatrix} \mu_{as} \\ \mu_{bs} \end{bmatrix} * Rate_{source} + \begin{bmatrix} \mu_{at} \\ \mu_{bt} \end{bmatrix} * Rate_{target} \tag{6}$$

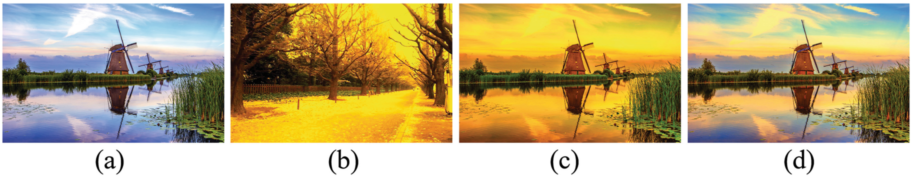

Fig. 6. Weight adjustment. (a) Target image (b) Source image (c) Transfer result (d) Weight adjustment

Where μ_{as}, μ_{at}, μ_{bs}, μ_{bt} denote the mean values of a and b channel in the source and target image respectively. We set weight coefficient $Rate_{source}$ and $Rate_{target}$ for the source and target image respectively to adjust the weight relationship between the images. Through this method, the luminance and chrominance of the result image have both the characteristic of the source image and the target image. As shown in Fig. 6, through the adjustment of the weight ratio, the result image has both the characteristic of the source image and the target image.

3 Experiments

Colorization is a hot issue in the field of image processing to adding color to a monochrome image. However, it's an expensive task to established chrominance mapping to convert an 8-bit monochrome image into a 24-bit color image automatically. Most existing methods need time-consuming and careful adjustment to obtain a good result [14]. By our method, since the foregrounds of the target image is extracted and matched to a source image using its texture features. The color transfer of the monochrome image foregrounds is constrained by the matching area in the source image. Hence, the reliability of the corresponding color transfer is improved owing to their homogenous textures. Figure 7 demonstrates a colorization example to illustrate the effectiveness of our approach. Figure 7(a) presents the target image and the user-specified segmentation to be adjusted. Then, a brush stroke is drawn in the region of interest. With its texture feature, the segment result with homogenous texture in the source image is obtained in Fig. 7(c). The transfer result is illustrated in Fig. 7(d). The color transfer makes a natural and reality effect. More examples are given in supplementary materials, different types of the target images are experimented using our approach, the results show a consistent effect with human visual experience.

Since the retrieved image is highly similar with the target image, the proposed approach achieves a favorable color style conversion. Some results are demonstrated in Fig. 8 (and supplementary materials).

The colorization on monochrome gets ideal results, similarly, our method can process the image that is lack of brightness as well. For instance, we could use our method on exposure adjustment. Although the underexposed image is poor in visual perception, the local luminance variation keeps enough details of the texture information. Hence, the proposed approach based on texture is fit for

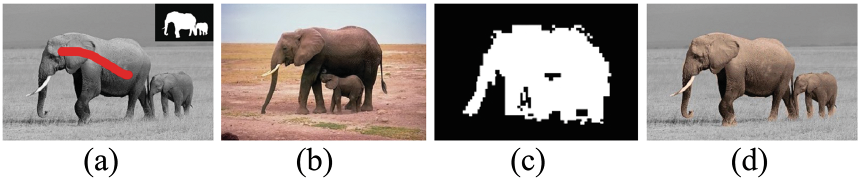

Fig. 7. Region mapping color transfer based on texture feature. (a) Target image with the mask and the interest area (b) Source image (c) Segment result (d) Transfer result

Fig. 8. Style conversion result. (a) Target image (b) Source image (c) Transfer result

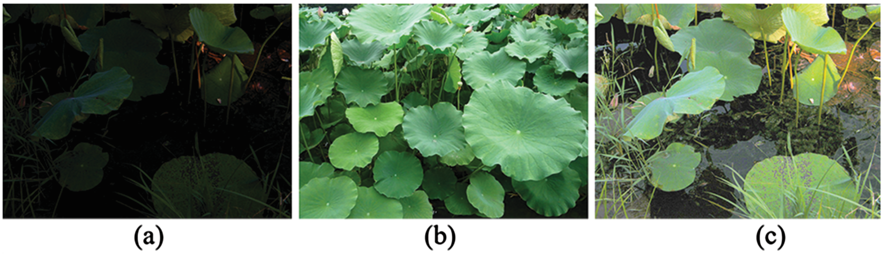

Fig. 9. Exposure adjustment. (a) Underexposed (b) Normal (c) Adjustment result

such situation. In contrast, luminance stretching used in many existing methods to adjust the brightness often produces a loss of details and an excessive contrast. With our method, the details of the image is preserving by the correspondence of the texture region in the case of transforming the brightness feature from the source image. As shown in Fig. 9 (and supplementary materials), the results are nature and have an excellent visual experience.

4 Conclusion

In this paper, a novel approach of homogenous color transfer based on texture retrieval and matching is proposed. A source image is selected according to the texture similarity to the target image. With a simple interaction of brush stroke on the target image, we get the regions of interest through artificial selection.

In order to search for the similar texture in the source image, we use a resizable window to segment the source image and withdraw the texture region. After that, the corresponding texture regions are extracted and mapped for the color transfer. In the experiments, we used our method to process the image colorization, style conversion and exposure adjustment. The experiments results demonstrate that our method can implement a realistic and natural visual effect.

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