Scene-Adaptive Color Transfer Model with Application for Image Compositing

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***Abstract*—Compositing is one of the most critical techniques in various aspects such as movie production and computer graphics. When images have complex textures, existing color based methods require exhaustive training samples to achieve plausible compositing results. In this paper, we propose a scene-adaptive color transfer model with an application for image compositing. We extract foregrounds from the source and target images. Then, we divide the source and target images into unequal bands according to the luminance. After that, color transfer is conducted by dynamically adjusting the weights of luminance and chrominance. To achieve a realistic composite, we introduce an adaptive source compositing region selection method and address the boundary transition by a discrete Poisson solver. The experiment results illustrate that our method achieves a faithful color transfer. In addition, our composite results appear highly realistic.**

***Keywords*-unequal division; weight adjustment; adaptive composite region; color transfer;**

I. Introduction

Color transfer is one of the most effective techniques to render realistic images. It has been widely used in film production to evoke certain emotions or reinforce a certain mood [1], such as The Grandmaster of Sil-Metropole Organization Ltd. and The Bullets Fly of Emperor Visual Product. The task of color transfer is mapping the color features of a source image to a target image. It can also be used to composite foreground of an image into another image with a seamless fusion. The effectiveness of color transfer affects the realism of compositing.

Color transfer methods using global statistics do not rely on the contents of images. These methods typically fails when the source and target images have different spatial distributions or styles. As a result, some methods incorporating local regions and user-assisted segmentations have been proposed. However, when the source and target images have significantly different distribution in luminance and chrominance, those methods may cause artifacts. As illustrated in Fig. 1, since the target image (Fig. 1(a)) of Titanic has salient luminance difference, the result image (Fig. 1(c)) of Bonneel et al.s method appears discontinuity and cannot retain local contrast.

In this paper, we propose a scene-adaptive color transfer model with application for image compositing, which

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

Figure 1: Comparison of equal pixel division and unequal pixel division: (a) target image, frame from Infernal Affairs; (b) source image, frame from A Chinese Odyssey; (c) color transfer result with equal pixel division; (d) color transfer result with adaptive pixel division. Video credits: Infernal Affairs (2002) (target), A Chinese Odyssey (1994) (source).

divides luminance channels into unequal bands and dynamically adjusts the weights of luminance and chrominance. We use the color consistency to extract foregrounds from the target image and compositing region from source image. Then, according to the luminance, we divide the source and target images into unequal bands and conduct color transfer between corresponding bands. To achieve a realistic fusion, we dynamically adjust the weights of luminance and chrominance. The main contributions of this paper are as follows.

(1) Propose a novel color transfer model with weight adjustment for scene adaption, which divides luminance channels into unequal bands and dynamically adjusts the weights of luminance and chrominance.

(2) Present a scene-adaptive image compositing, which selects source composite regions adaptively and adds interesting objects into composite scenes by our color transfer model.

The remainders of this paper are organized as follows: Section 2 presents related work in color transfer and scene fusion. Section 3 introduces the color transfer model including the unequal pixel division and weight adjustment.

Section 4 introduces the adaptive selection of the compositing region and scene fusion. Our experiment results are illustrated in Section 5, and Section 6 draws a conclusion.

II. Related work

Color transfer techniques have attracted increasingly attention since Reinhard et al. [2] proposed the decorrelated color space and used two features to present the mean value and deviation of each channel. Pitie et al. [3] focused on global color distribution using Probability Distribution Function. However, when matching regions have different spatial distributions, the global methods may cause serious artifacts.

In order to deal with local contrast, some methods incorporating local regions and user-assisted segmentations have been proposed. Pitie et al. [4] proposed the best linear color transformation using Monge-Kantorovicth theory in mass transportation area. Tai et al. [5] applied an Expectation-Maximization model to optimize local color matching by probabilistic segmentation. An et al. [6] allowed user to specify regions by strokes and then make color transfer between the specified regions. Pouli et al. [7] used the reshaped histogram at different scales to transfer color palette between images at arbitrary dynamic range. HaCohen et al. [8] presented a method that uses Generalized PatchMatch and coarse-to-fine scheme to enhance correspondence regions between two images with shared content. Bonneel et al. [9] proposed an example-based video color grading method, which uses a mixed color transfer model for luminance and chrominance.

However, when the source and target images have significant difference in luminance and chrominance distributions, most existing color transfer methods are apt to cause artifacts. In this paper, we propose a scene-adaptive color transfer model with application for image compositing, which uses unequal pixels division in luminance bands and dynamically adjust the luminance and chrominance weights to improve the realism of visual perception.

Color transfer has already received some attention in scene composite. Johnson et al. [10] used a large number of images collected from online repository and conducted region matching between CG and real images by a mean-shift segmentation algorithm. Xue et al. [11] proposed a data-driven method which introduces some statistical measures to denote the realism of compositing and then adjust the luminance and chrominance of an interesting region accordingly. Unfortunately, these methods require numerous training samples, and the best sample matching is an exhaustive process. In this paper, our compositing method utilizes the luminance and chrominance consistency to transfer the color of a fusion region in the source image to an interesting region in the target image. It is proved to be highly realistic in the final fusion results.

Compared with the existing color transfer methods, our transfer model adaptively adjusts the weights of luminance and chrominance and considers both the color features of interesting objects and composite scenes.

III. Color Transfer Model

In this section, we propose a scene-adaptive color transfer model applying characteristics of a source image to a target image. We use a cumulative histogram method to maintain the luminance contrast within the source image. Then, we divide the source and target images into unequal bands and conduct chrominance transformation for each luminance bands. For the color space, we follow the recommendation of Reinhard and Pouli [8] and work in CIE-Lab and the D65 illuminant.

A. Luminance Transformation

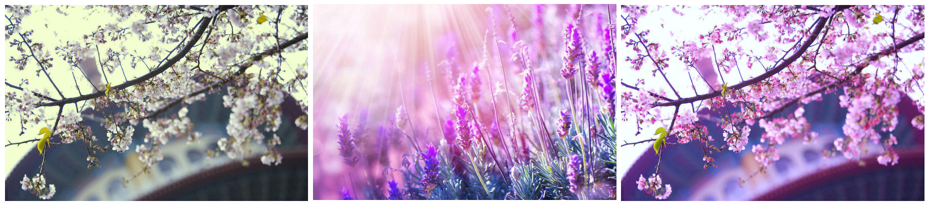
We use the standard cumulative histogram method [12] to transfer the luminance features of a source image to a target image. The standard histogram transfer function is defined as $L_t = H^{-1}(T_l)$, where the operator H denotes the normalized luminance cumulative distribution function, T_l denotes the cumulative probability under the specified value in channel L within the target image, and L_t denotes the transferred value. We then remap the luminance of the source image to the target image using the inverse function of H. Specifically, we use the generalized inverse [13] when the cumulative distribution function is not invertible.

Considering that two matching images may have serious noises (i.e., low-quality image input) or significantly different distributions (i.e., salient contrast), we apply the Gaussian filter to prevent extreme histogram stretching.

B. Chrominance Transformation

Since the equal pixel division may cause uncontinuous artifacts, especially when the source image and target image have salient different spatial distributions, our chrominance transformation separates the source and target image into unequal pixel bands according to the luminance. We use the K-medoids clustering method [14] to divide the pixels of the source and target images into multiple clusters, respectively. Then, for each cluster, we choose a representative luminance value among its member pixels. The clustering results of K-medoids are regarded as the initial classifications of pixels within the source and target images.

After K-medoids clustering, two features of each cluster will be stored in a two-tuple $[\overrightarrow{V}, \overrightarrow{N}]_m$, where $\overrightarrow{V}$ denotes the vector of representative luminance values, $\overrightarrow{N}$ denotes the vector of pixel number within the clusters, and m denotes the total number of clusters. Accordingly, the representative luminance value and the pixel number of the i-th cluster are stored as the i-th components of $\overrightarrow{V}$ and $\overrightarrow{N}$, respectively.Based on $\overrightarrow{N}$, the clusters with frequency less than are merged with their neighbors. Typically, a value of 0.1 is used



(a) (b) (c)

Figure 2: Unequal chrominance transformation: (a) target image, (b) source image, and (c) color transfer result.

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

Figure 3: Color transfer without and with fore-background segmentation: (a) target image, (b) source image, (c) global transfer without segmentation, and (d) local transfer with segmentation. Video credits: Titanic (1994) (Target), Schindler's List (1993) (Source).

as an empirical cut-off value of σ. Then, according to $\overrightarrow{V}$, we compute the average intra-cluster luminance difference $d(C)$ for each cluster C and merge the clusters with $d(C)$ less than Δ. The value of Δ is typically set as 0.33. Finally, we obtain three clusters of the source and target images, respectively, and regard them as the final luminance bands.

According to the representative band value, we pair a band of the source image with a band of the target image. For each pair of bands, we compute the mean values and covariance matrix of a and b channels in Lab, respectively. The mean values of a and b form a bivector $[\mu_a, \mu_b]^T$, and the covariance matrix is a 2×2 square matrix [15]. Then, we apply the linear Monge-Kantorovitch linear color mapping [4] to transfer the chrominance a_t and b_t of a source image pixel to the corresponding $a_t^{'}$ and $b_t^{'}$. The chrominance transformation is computed as

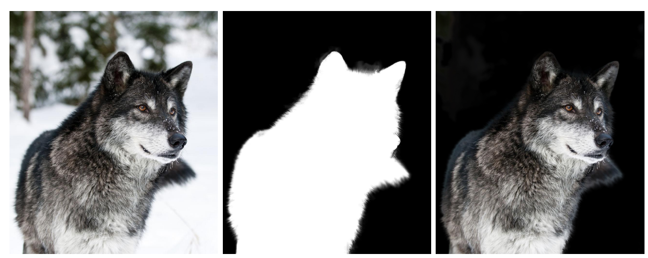
$$\begin{bmatrix} a_t^{'} \\ b_t^{'} \end{bmatrix} = T_{st} \begin{bmatrix} a_t - \mu_{at} \\ b_t - \mu_{bt} \end{bmatrix} + \begin{bmatrix} \mu_{as} \\ \mu_{bs} \end{bmatrix} \quad (1)$$

where μ_{as} and μ_{bs} denote the mean values of a and b in the source image respectively, μ_{at} and μ_{bt} denote the mean values of a and b in the target image respectively, and T_{st} denotes the chrominance transformation matrix. The matrix T_{st} is defined as

$$T_{st} = \sum\nolimits_t^{-1/2} \left(\sum\nolimits_t^{-1/2} \sum\nolimits_s \sum\nolimits_t^{-1/2}\right)^{1/2} \sum\nolimits_t^{-1/2} \quad (2)$$

where $\sum_s$ and $\sum_t$ denote the covariance matrices of the source and target images, respectively. The result of chrominance transfer is illustrated in Fig. 2, in which the chrominance of the source image is remapped to the target image.

C. Foreground-background Segmentation



(a) (b) (c)

Figure 4: Fore-background segmentation. (a) Input image. (b) Matte image. (c) Foreground image. Fore-background segmentation maintains local style in the source image. In (b), we make a matte for the wolf and refine the matte using tri-map method. Then, in (c), we obtain the foreground of the input image.

We employ a user-specified segmentation to extract foreground objects from a background image, especially when a source image has significant local contrasts. Fig. 4 gives an example to show the significance of segmentation for color transfer. As Fig. 3(c) shows, the color transfer without foreground-background segmentation only uses the global luminance and chrominance, and the transferred result loses the local style of the source image.

We create an initial matte using the segmentation method proposed by Bai et al. [16] to create an initial matte. This method uses a set of local classifiers to integrate multiple local image features and extracts foreground objects by the collaboration of the classifiers. Then, we erode and dilate

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

Figure 5: Color transfer with weight adjustment: (a) target image, (b) source image, (c) color transfer result without weight adjustment, and (d) color transfer result with weight adjustment.

the initial matte and obtain two mattes as the input of the matting method proposed by Levin et al. [17]. This matting method obtains a globally optimal matte by solving a sparse linear system of equations. Fig. 4 shows the segmentation results of fore-background.

D. Weight Adjustment for Scene Adaption

When compositing an object into a scene, we must incorporate both the color features of the object and the composite scene. The correlation of luminance and chrominance affect the realism of composited results in visual perception. We adaptively adjust the weights of luminance and chrominance according the color difference between the source image and target image.

The difference of luminance between the source image S and target image T is defined as

$$C_L(S,T) = \sum_m \|\mu_{Sl}^m - \mu_{Tl}^m\|^2 \tag{3}$$

where m is the number of luminance bands, μ_{Sl}^m and μ_{Tl}^m denote the mean luminance values of the m-th band within F and B, respectively.

The difference of chrominance between the source image S and target image T is computed by

$$C_{ab}(S,T) = \sum_m tr(\sum{}_S^m + \sum{}_T^m - 2(\sum{}_S^{m^{1/2}} \sum{}_T^m \sum{}_S^{m^{1/2}})^{1/2}) + \|\mu_{Sab}^m - \mu_{Tab}^m\|^2 \tag{4}$$

where m is the number of luminance bands, $\sum_S^m$ and μ_{Sab}^m denotes the covariance matrix and the mean chrominance values of the m-th band within S respectively, and $\sum_T^m$ and μ_{Tab}^m denotes the covariance matrix and the mean chrominance values of the m-th band within T respectively.

For target image T, We compute the mean luminance value as MLT and the mean chrominance values as MaT and MbT, respectively. Then, we use the proposed luminance and chrominance transfer and remap T to T.Based on T, which is the initialization of target image color transfer, we adjust the weights of luminance and chrominance to generate the final transfer results. The pseudocode of our weight adjustment for scene adaption is described as Algorithm 1.

Algorithm 1 Weight Adjustment for Scene Adaption

Input: S: the source image, T': the transferred target image.
Output: T': the adjusted image.

InitializeColorFeatures(MLT', MaT', MbT')
InitializeColorFeatures(MLS, MaS, MbS)
α = 0.1 // The scale of difference between S and T.
β = 0.001 // The scale of color feature update.
while $\|C_L(T,T')+C_{ab}(T,T')\| > \alpha\|C_L(S,T) + C_{ab}(S,T)\|$ **do**
  (MLT'', MaT'', MbT'') = (MLT', MaT', MbT')
  MLT = *UpdateLuminance*(T', β)
  MaT = *UpdateChrominancA*(T', -β)
  MbT = *UpdateChrominancB*(T', -β)
  if $\|C_L(T,T')+C_{ab}(T,T')\| > \|C_L(T,T'') + C_{ab}(T,T)\|$ **then**
    T = T''
  else
    MLT' = *UpdateLuminance*(T', -β)
    MaT' = *UpdateChrominancA*(T', β)
    MbT' = *UpdateChrominancB*(T', β)
  end if
end while

Our weight adjustment algorithm uses the difference $\alpha\|C_L(S,T) + C_{ab}(S,T)\|$ of source image S and target image T to adjust the color of the transferred target image T'. The algorithm terminates when the difference $\|C_L(T,T')+C_{ab}(T,T')\|$ of T and T' is less than $\alpha\|C_L(S,T) + C_{ab}(S,T)\|$. The adjusted image T' involves both features of the source image and target image. Fig. 5 illustrates the transferred result with the dynamic weight adjustment of luminance and chrominance.

IV. Scene-Adaptive Image Compositing

When adding foregrounds extracted from a target image into a composite image, we must keep the color consistency between foregrounds and backgrounds of the composited image. The compositing region is adaptively selected according to the seed point. Then, the color features of the region are transferred to the foregrounds. After that, we use the Poisson image editing to make smooth transition from the foregrounds to the composite image.

A. Adaptive Source Composite Region Selection

We propose an adaptive source region selection method, which starts from a seed point and extends the region according to the color consistency of boundary pixels. After a seed point R is given, which represents the position of the foreground in the composite image, we initialize the composite region Ω as the area around R covered by the interesting objects matte. The boundary of Ω is defined by $\partial\Omega = \{p \in \Omega \,|\, N_p \cap \Omega \neq \emptyset\}$, in which p denotes the boundary pixels and N_p denote the 4-connected neighboring pixels of p.

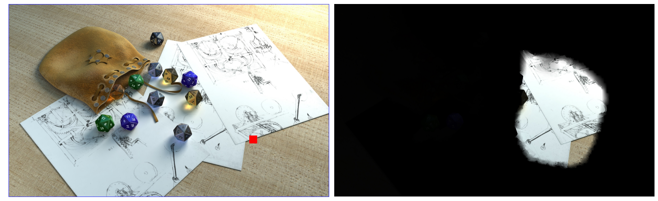
The seed point denotes the position to locate the foreground of the target image which illustrated as red square point in Fig. 6(a) and initialized compositing region is the defined as the region covered by the interesting objects matte. Then we use Ω to denote the initial compositing region and use N_p to signify the set of its 4-connected neighbors which are in Ω. So the boundary of Ω is $\partial\Omega = \{p \in \Omega \,|\, N_p \cap \Omega \neq \emptyset\}$. The pseudocode of our adaptive composite region selection is described as Algorithm 2.

Algorithm 2 Adaptive Composite Region Selection

Input: S: the source image, TM: the matte of an interesting object.
Output: F: the composite region in composite image.

Λ = *BoundaryPixelSet*(TM)
$F = \Lambda$
α = 0.35 // The threshold to decide whether to add a pixel.
while *IsNotEmpty*(Λ) **do**
  p = *PickOnePixel*(Λ)
  Υ = Neighbors(p)
  while *IsNotEmpty*(Υ) **do**
    q = PickOnePixel(Υ)
    $E = \frac{1}{m} \sum_{p \in \Lambda} (p_L + p_a + p_b)$
    if $\|q_L + q_a + q_b - p_L - p_a - p_b\| < \alpha E$ **then**
      $\Lambda = \Lambda \cup q$
      $F = F \cup q$
    end if
  end while
end while

Our adaptive compositing region selection expands the boundary pixel set Λ of an interesting object to generate the final region F. The algorithm picks one pixel p from Λ and adds the neighbors of pixel p to Λ according to the average color energy $E = \frac{1}{m} \sum_{p \in \Lambda} (q_l + q_a + q_b - p_L - p_a - p_b)$. Fig. 6 illustrates the adaptive selection result of the compositing region by our method.

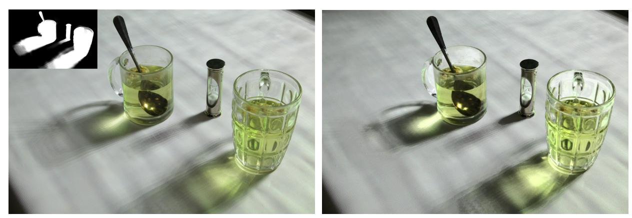


(a) (b)

Figure 6: Adaptive compositing region selection: (a) composite image, and (b) the source compositing region. (The red point denotes the position to locate the interesting objects)

B. Image Compositing

We remap the luminance and chrominance of an interesting object to the compositing region by our color transfer model. The transferred result with our dynamic weight adjustment is illustrated in Fig. 7.

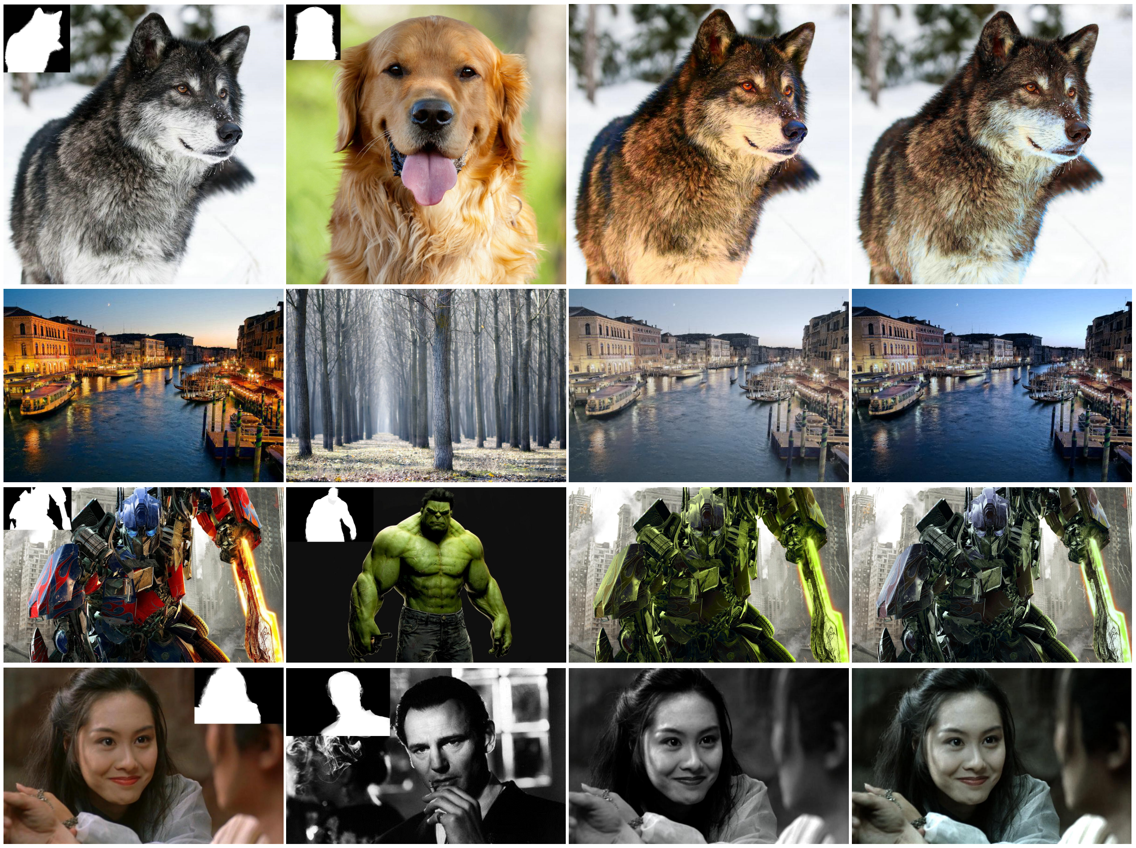


(a) (b)

Figure 7: Dynamic weight adjustment result of the objects: (a) the original objects, and (b) the transferred objects with weight adjustment.

Figure 8: Composite result which adds a cup from target image into the composited image.

To achieve highly realistic visual effect, we must make smooth transition on the boundary of the composite region. We build the boundary mask of the interesting object by a Breadth First Search algorithm with a path length threshold $\min\{\max\{D_p\}, \sigma \cdot \min\{W, H\}\}$, where D_p denotes the distance from pixel p to seed point R, W and H denote



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

Figure 9: Results of our color transfer method. (a) Target image. (b) Source image. (c) Color transfer results without weight adjustment. (d) Color transfer results with weight adjustment.

the lengths of the object in horizontal and vertical directions, respectively. Typically, σ is set to 0.1 as the empirical value.

For image compositing, we use the Possion image editing method proposed by Farbman et al. [18] to create plausible transition on the boundary between the foregrounds and backgrounds. Let S denotes the composite image, f^* denotes a known scalar function defined outside the composite region Ω, f denotes an unknown scalar function defined inside the composite region Ω, and g denotes a known scalar function defined in the interesting objects of the target image. Then, the boundary transition is formulated as an optimization problem:

$$\min_{f} \iint_{\Omega} \|\nabla f - \nabla g\| \;\; s.\,t.\; f|_{\partial\Omega} = f^*|_{\partial\Omega} \tag{5}$$

where ∇ is he gradient operator. Then, the optimization problem is solved by a discrete Poisson solver, and the interesting object is fused into the composite image naturally in visual perception. Fig. 8 shows the composited result of our method. We add a cup into an image, and the composited image appears highly realistic and natural.

V. Experiments & Results

To evaluate the effectiveness our color transfer method, we apply it to several image pairs from online repositories and conduct experiments on a computer of Intel Xeon(R) CPU at 3.06GHz and 6G RAM. The color transfer results are shown in Fig. 9. Fig. 9(a) illustrates the column of target images, Fig. 9(b) illustrates the column of source images, Fig. 9(c) illustrates the transferred images without weight adjustment and the results with weight adjustment are illustrated in Fig. 9(d). It is clearly shown that the transferred images in Fig. 9(d) involve both features of the source images and the target images.

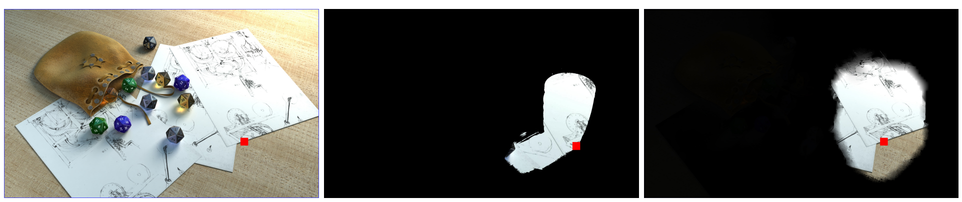
Compared with the color transfer method proposed by Bonneel et al., which divides pixels into even bands, our method shows superior performance. As shown in Fig.10, our method achieves a more faithful result even when the luminance distributions of a source image and a target image are significantly different. The main reason is that our method divides pixels into several unequal bands by luminance clustering and maintains the consistency in the mapping.

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

Figure 10: Contrast between even division based color transfer and our unequal division based color transfer. (a) Target image. (b) Source image. (c) Equal division result. (d) Unequal division result.

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

Figure 11: Comparison of composites: (a) target image, (b) background scene, (c) composited result without color transfer, (d) composited result using color transfer without weight adjustment, and (e) composited result with our weight adjustment based color transfer.



(a) (b) (c)

Figure 12: Composite regions selected by different strategies: (a) entire compositing image selected as the composite region, (b) the region selected by a naive method, and (c) the region selected by our method. (The red point in (a) denotes the position to locate the interesting objects.)

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

Figure 13: Color transferred objects and the corresponding composited images: (a) original objects without color transfer, (b) objects transferred with the entire compositing image as the composite region, (c) objects transferred with the composite region selected by a naive method, and (d) objects transferred with the composite region selected by our method.

We also apply our weight adjustment based color transfer method to add interesting objects into an image, and Fig. 11 shows the composited results. Compared with the composited results in Fig. 11(c) and Fig. 11(d), the effectiveness of the weight adjustment can be clearly seen, and the result in Fig. 11(e) appears highly realistic in visual perception. Our transfer method considers both the color features of the interesting objects and composite image, and thus achieves a realistic composite result.

The selection of the compositing region significantly affects the realism of the composited image. Fig. 12 shows the compositing regions selected by different strategies. In Fig. 12(a), the entire image is considered as the compositing region. In Fig. 12(b), a naive method is employed for region selection, which only uses the matte of an interesting object as the compositing region. Fig. 12(c) shows the result of our composite region selection, which considers both the color distribution of a composite image and the color similarity between an interesting object and the image. Accordingly, Fig. 13 shows the color transferred interesting objects and the corresponding composited images. From the results of Fig. 13, the composited images with our region selection method demonstrates a more realistic and natural looking.

VI. Conclusion

A novel scene-adaptive color transfer model is proposed in this paper. In this model, foregrounds are extracted from the source and target image. Then, we divide the source and target images into unequal bands according to the luminance. After that, color transfer is conducted by dynamically adjusting the weights of luminance and chrominance. To achieve a realistic compositing, the compositing region is selected adaptively and the boundary transition is addressed by a discrete Poisson solver. The experiment results demonstrate that our method achieves faithful color transfer and realistic compositing.

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