Color Transfer in Correlated Color Space

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(a) Source image   (b) Target image   (c) Result image

Figure 1: Conveying the color characteristic of a warm-tone photograph (a) to a cold-tone one (b) in RGB color space.

Abstract

In this paper we present a process called color transfer which can borrow one image's color characteristics from another. Recently Reinhard and his colleagues reported a pioneering work of color transfer. Their technology can produce very believable results, but has to transform pixel values from RGB to $l\alpha\beta$. Inspired by their work, we advise an approach which can directly deal with the color transfer in any 3D space.

From the view of statistics, we consider pixel's value as a three-dimension stochastic variable and an image as a set of samples, so the correlations between three components can be measured by covariance. Our method imports covariance between three components of pixel values while calculate the mean along each of the three axes. Then we decompose the covariance matrix using SVD algorithm and get a rotation matrix. Finally we can scale, rotate and shift pixel data of target image to fit data points' cluster of source image in the current color space and get resultant image which takes on source image's look and feel. Besides the global processing, a swatch-based method is introduced in order to manipulate images' color more elaborately. Experimental results confirm the validity and usefulness of our method.

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1 Introduction

Recently there were several important works about color alteration introduced to computer graphics community, including color transfer[Reinhard et al. 2001] and colorization[Welsh et al. 2002][Levin et al. 2004][Ironi et al. 2005] and its reverse processing[Gooch et al. 2005]. Color transfer is a kind of process of color alteration, which changes an image's color to accord with another image's color characteristics. Applications of color transfer range from subtle post-processing on images to improve their appearance to more dramatic alterations, such as converting a daylight image into a night scene.

Reinhard and his colleagues presented a pioneering work about color transfer[Reinhard et al. 2001]. Because of the correlations between the three channels' values in RGB color space, they transform pixels' values from RGB to $l\alpha\beta$, and then manipulate them separately, and finally return to RGB space. Their method can produce amazing results.

Inspired by the work of Reinhard et al, we also explore color transfer, but focus on manipulating directly images' color in RGB space. From the view of statistics, we consider pixel's value as a three-dimension stochastic variable and an image as a set of samples, so the correlations between three components can be measured by covariance. Meanwhile, the mean along each of the three axes of RGB space is calculated. Our approach alters target image's color through a series of transformations that include translation, scaling and rotation, derived from these statistics—mean and covariance of the target and source images. The translation and scaling procedures are similar to Reinhard et al's, and rotation follows a matrix obtained by decomposing the covariance matrix using SVD algorithm. Finally, we get a resultant image that takes on source image's look and feel but target image's scene. Figure 1 shows an example which exhibits successfully conveying the warm-tone color charac-

teristic from source image to target image. All processing is done in RGB color space.

A swatch-based transfer algorithm is proposed for more user intervention, which can provide flexibility for users selecting desired swatches in one or more than one image, and the target image's color can be more elaborately manipulated.

In some cases, we extend color transfer to 3D correlated color space where our solution adds rotation into Reinhard et al's transformations to resolve the problem of correlation between three components. Our method can produce believable results while the simplicity is reserved.

1.1 Related Work

Color alteration is an active research area in the communities of image processing and computer graphics. The researches much related with our work in the area of color alteration include color transfer, color correction, colorization of grayscal images and its reverse processing.

In a recent pioneering work Reinhard and his colleagues introduced a method for color transfer between images[Reinhard et al. 2001]. Applications of Reinhard et al's work range from subtle postprocessing on images to improve their appearance to more dramatic alterations, such as converting a daylight image into a night scene. First, they convert pixel values in RGB color space to Ruderman et al's perception-based color space $l\alpha\beta$[Ruderman et al. 1998]. Then, they calculate the mean and standard deviations along each of the three axes, and then scale and shift each pixel in the input image. Last, they transform pixel values to return to RGB space. While this method has produced some very believable results, it is restricted in $l\alpha\beta$ color space.

Color correction techniques have been proposed in a number of literature. [Gasparini and Schettini 2003] introduce a reliable and rapid method of color correction for digital photographs on the CIELab color space. Their algorithm can detect and remove a color cast in a digital image without any a priori knowledge of its semantic content. [Watanabe et al.] et al propose a neural network model trained by genetic algorithm to realize color correction. Their approach is qualitatively and quantitatively superior to the conventional color correction. Another color correction method has been developed by Schechner and Karpel for underwater imaging and great improvement of scene contrast and color correction are obtained[Schechner and Karpel 2004]. Jia et al propose a color correction approach based on a Bayesian framework to recover a high-quality image by exploiting the tradeoff between exposure time and motion blur[Jia et al. 2004].

Colorization is a term that is now used generically to describe any technique for adding color to monochrome stills and footage. Welsh et al introduce a general technique for colorizing greyscale images by transferring color between a source, color image and a destination, greyscale image[Welsh et al. 2002]. Their method transfers the entire color mood of the source to the target image by matching luminance and texture information between the images and allows user interaction. [Levin et al. 2004] presents a simple colorization method that requires neither precise image segmentation, nor accurate region tracking. Their method is based on a simple premise: neighboring pixels in space-time that have similar intensities should have similar colors. An algorithm for the reverse processing of colorization is proposed by Gooch et al [Gooch et al. 2005]. By attempting to preserve the salient features of the color image, Gooch's algorithm can reduce the losses of visually important image features when color images are converted to grayscale.

2 Statistics-based Method

Our goal is to produce an image that has target image's scene but takes on source image's look and feel. This means that we must express the important subjective notions of style and appearance in images using some mathematical terms and handle them. Studies by Reinhard and his colleagues have found that straightforward color statistics can capture these subjective notions of style and appearance in images[Trumblin and Ferwerda 2001]. Their article shows how to transfer them from one image to another for copyimg color characteristics using the mean and standard deviation in $l\alpha\beta$ color space. For our purpose, we develop a statistics-based method that can achieve the goal in RGB color space just utilizing the statistics—mean and covariance matrix. Here the covariance matrix can be deemed to the extension of standard deviation in correlated space. The essence of our method is moving data points of source image by scaling, rotation and translating to fit data points' cluster of target image in RGB color space.

In this section we introduce how to do color transfer using the two statistics. More subtle manipulating on images will be discussed in the next section.

First, we calculate the mean of pixel data along the three axes and the covariance matrix between the three components in color space for both the source and target images. All of the statistics are denoted by $(\overline{R}_{src}, \overline{G}_{src}, \overline{B}_{src})$, $(\overline{R}_{tgt}, \overline{G}_{tgt}, \overline{B}_{tgt})$, Cov_{src} and Cov_{tgt}, respectively.

Then, we decompose the covariance matrices using SVD algorithm[Konstantinides and Yao 1988], namely,

$$Cov = U \cdot \Lambda \cdot V^T$$

where U and V are orthogonal matrices and are composed of the eigenvectors of Cov, $\Lambda = diag(\lambda^R, \lambda^G, \lambda^B)$ and λ^R, λ^G and λ^B are the eigenvalues of Cov. We employ U as a rotation matrix to manipulate pixels of the source image in the next step.

Last, we do a transformation as follows:

$$I = T_{src} \cdot R_{src} \cdot S_{src} \cdot S_{tgt} \cdot R_{tgt} \cdot T_{tgt} \cdot I_{tgt} \tag{1}$$

where $I = (R, G, B, 1)^T$ and $I_{tgt} = (R_{tgt}, G_{tgt}, B_{tgt}, 1)^T$ denote the homogeneous coordinates of pixel points in RGB space for the result and target images respectively; T_{src}, T_{tgt}, R_{src}, R_{tgt}, S_{src} and S_{tgt} denote the matrices of translation, rotation and scaling derived from the source and target images separately. Here is their definitions:

$$T_{src} = \begin{pmatrix} 1 & 0 & 0 & t_{src}^r \\ 0 & 1 & 0 & t_{src}^g \\ 0 & 0 & 1 & t_{src}^b \\ 0 & 0 & 0 & 1 \end{pmatrix}, T_{tgt} = \begin{pmatrix} 1 & 0 & 0 & t_{tgt}^r \\ 0 & 1 & 0 & t_{tgt}^g \\ 0 & 0 & 1 & t_{tgt}^b \\ 0 & 0 & 0 & 1 \end{pmatrix}$$
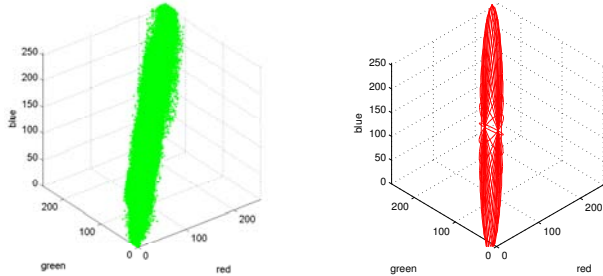
$$R_{src} = U_{src}, R_{tgt} = U_{tgt}^{-1}$$

$$S_{src} = \begin{pmatrix} s_{src}^r & 0 & 0 & 0 \\ 0 & s_{src}^g & 0 & 0 \\ 0 & 0 & s_{src}^b & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, S_{tgt} = \begin{pmatrix} s_{tgt}^r & 0 & 0 & 0 \\ 0 & s_{tgt}^g & 0 & 0 \\ 0 & 0 & s_{tgt}^b & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$
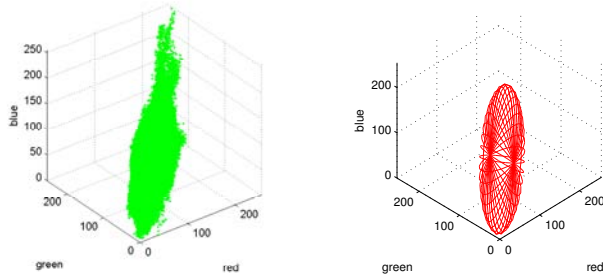
where $t_{src}^r = \overline{R}_{src}$, $t_{src}^g = \overline{G}_{src}$, $t_{src}^b = \overline{B}_{src}$, $s_{src}^r = \lambda_{src}^R$, $s_{src}^g = \lambda_{src}^G$, $s_{src}^b = \lambda_{src}^B$, $t_{tgt}^r = -\overline{R}_{tgt}$, $t_{tgt}^g = -\overline{G}_{tgt}$, $t_{tgt}^b = -\overline{B}_{tgt}$, $s_{tgt}^r = 1/\sqrt{\lambda_{tgt}^R}$,
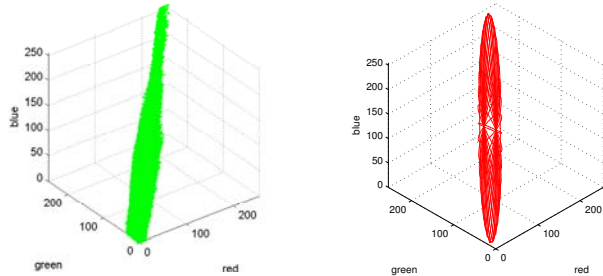
(a) Source image   (b) Target image   (c) Result image

(d) Points cluster and fitting ellipsoid for the source image

(e) Points cluster and fitting ellipsoid for the target image

(f) Points cluster and fitting ellipsoid for the result image

Figure 2: Statistics-based color transfer in RGB color space. The fat fitting ellipsoid of target image is morphing to fit the thin one of source image.

$s_{tgt}^g = 1/\sqrt{\lambda_{tgt}^G}$, and $s_{tgt}^b = 1/\sqrt{\lambda_{tgt}^B}$. The subscripts of $_{src}$ and $_{tgt}$ represent for source image and target image, respectively.

All in all, the transformations depicted above simulate morphing an ellipsoid to fit another one. The two ellipsoids separately fit the pixel points of source and target images in color space. The fitting of ellipsoid extends the method of fitting ellipse in 2D space[Lee 2002] and involves computing the mean and the covariance matrix. The mean is the center coordinates of an ellipsoid, and the eigenvalues and eigenvectors of the covariance matrix indicate the length and orientation of the three axes of the ellipsoid. The transformations act on all of the pixels in the target image and move them to appropriate positions in color space. Figure2 illustrates to borrow an autumn photo's color characteristics from an summer photo and shows the points clusters and fitting ellipsoids for the source, target and result images.

The statistics-based color transfer method can naturally extend to any 3D color space through replacing R, G and B with three com-

ponents in another color space.

3   Swatch-based Transfer

The statistics-based method depicted above demonstrates a global processing. When we transfer one image's appearance to another, it's possible to select source and target images that don't work well together. The result's quality depends on the images' similarity in composition. For example, if the target image contains much sky, trees and other scene and the source image has more grass and a marble handrail in it, then we can expect the global statistics-based method to fail (figure 3(c)). We say it fails when the result image haven't the source image's feel and look. That is, source image with desired look fails to transfer its color characteristic to target image. So some remedy are necessary. Reinhard et al encountered the same problem. They devised a swatch-based method to resolve it. We formulate their approach and provide some parameters for more flexible user interaction.

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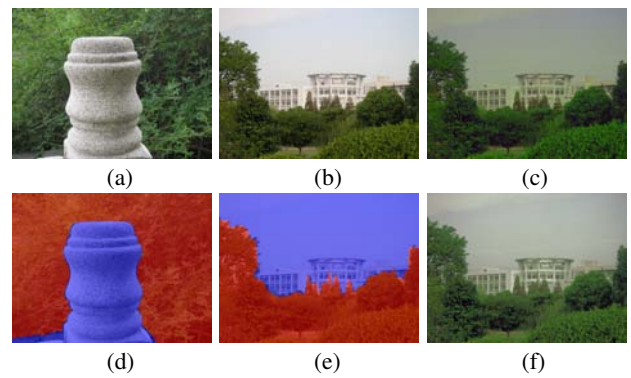
(d)   (e)   (f)

Figure 3: Swatch-based color transfer: roughly marking swatch pairs from source and target images, producing intermediate results corresponding to different target swatches, and merging the intermediate results through calculating weighted sums. Source image(a) and target image(b); failed global transfer(c); rough masks of the source(d) and target(e) images; good result(f).

Actually, our swatch-based transfer method is a simple operation. First, we can select separate swatches from the source and target images by just roughly marking swatch pairs with same colors. Naturally we can select swatches as desired effects from one or more images. In this step, we only partition images into separate zones roughly and don't sculpt the edge of zones accurately. Then, we calculate swatches' statistics—the mean and covariance matrices and transfer target image for the different swatch pairs using the algorithm depicted in the section 2 and obtain several corresponding intermediate images. Then, we compute the distances from each pixel in the intermediate images to the center of each fitting ellipsoid of target swatch data. We blend the pixels with same coordinates in separate result images with weights inversely proportional to these distances, yielding the final color. The blending processing can be expressed as a equation:

$$I = \sum_{i=1}^{m} \sum_{j=1}^{n} a_i \cdot w_{ij} \cdot I_j \qquad (2)$$

where $I = (R, G, B)^T$ is the final result's color, w_{ij} are the weights according to the distances between pixel data and the center of swatches, $I_j = (R_j, G_j, B_j)^T$ are the intermediate images' data corresponding to separate target swatches, m and n are the numbers

of swatches in the source and target images ($m = n$ in our work), and a_i are weights that can be adjusted by users but $\sum_{i=1}^{m} a_i = 1$ and $a_i \geq 0$. Figure 3(f) shows the result and the selection of swatches in the source and target images.

Theoretically, the number of swatch pairs is unlimited but two and three are enough for most pictures. Indeed two or three swatch pairs are efficient for calculation.

4 Results

It is very hard to evaluate results objectively, the evaluation is really subjective. The results shown here were all obtained using the simple transformation represented by Equation 1 and the combining formula (Equation 2). The algorithm's simplicity makes it running in real-time for 800×600 size images.

Figure 1 and 2 showcase the effectiveness of our method for borrowing one image's color characteristics from another directly in RGB color space.

In some cases, such as figure 3, the global transfer may fail because of the dissimilarity in composition between the source and target images. Reinhard et al encountered the same condition. So we develop the swatch-based method to remedy this issue. We make a formula and provide some parameters for more flexible user interaction. Figure 3(f) shows an approving result. Now the result image looks like the source's feel. Normally we set the parameters a_i as the ratio of the corresponding swatch's area in the whole.

In figure 4 we show two examples for the compare of effects which come from Reinhard's algorithm and our method in RGB and $l\alpha\beta$ spaces respectively. Just as we see, Our results are very believable as the same as Reinhard's. It is worth mention that the masks just are marked roughly.

5 Summary

In this paper, we discuss a color transfer method that can borrow one image's color characteristics from another in any three dimension color space directly. Imposing mean and covariance onto the data points is a very simple operation, which produces believable output images given suitable input images.

Actually, our approach is the extension of Reinhard's. We eliminates the transformations between color spaces and formulate the swatch-based transfer to provide parameters for user interaction.

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(a)   (b)

(c)   (d)   (e)

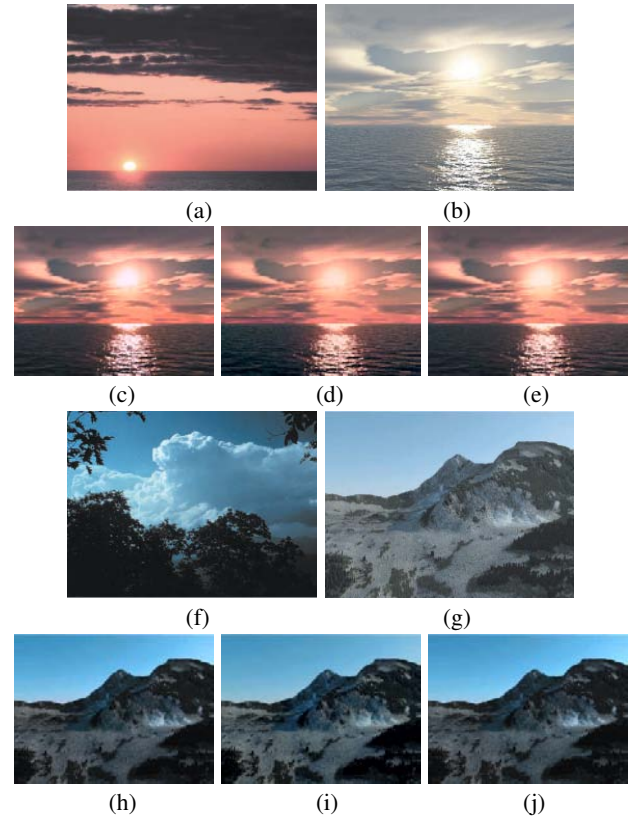(f)   (g)

(h)   (i)   (j)

Figure 4: Two examples for effects contrast. The source images (a, f) and the target images (b, g); The results from Reinhard's method (c, h); The results of our method operated in RGB space (d, i); The result of our method operated in $l\alpha\beta$ space (e, j).

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