Color Transfer Between Images

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***Abstract*—Color transfer is a method in image processing where an image can acquire color characteristics of another image. The color characteristics of the source image are modeled using its statistical properties and are then transferred to the target image. This paper will present a detailed understanding and implementation of the work done by Xuezhong Xiao et al. in [1].**

I. Introduction

A color image consists of three different matrices namely red, green and blue, each of which can be considered as a stochastic variable. If we plot these three variables along red, green and blue axes in space, we get a plot as shown in Figure 1.

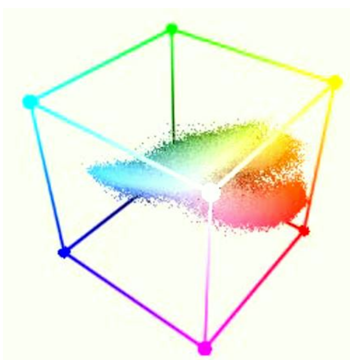

Fig. 1. Color Cube

It can be clearly seen that the three set of variables are correlated to each other. As we will see in the later section, this correlation between the red green and blue frames of an image will be the used as a key to model an ellipse which is used in transferring color characteristics to another image.

II. Background

The following topics are fundamental in understanding the ellipse modeling. For the sake of simplicity, we will consider 2D data distribution here.

A. Covariance Matrix of stochastic variables

Variance of a variable is a measure of the spread of the data in the direction of the variable itself. Also if two variables are correlated, then there exists a covariance between them. This notion can be visualized from Figure 2, where (a) shows that x and y are uncorrelated and thus the covariance matrix Σ has only diagonal elements i.e. variance in x or y direction. However in Figure 2(b), x and y are correlated and thus we have covariance values along non-diagonal elements and variance along diagonal elements. Note that, data represented with two variables gives 2x2 covariance matrix, thus for N dimensional data, the covariance matrix will be NxN.

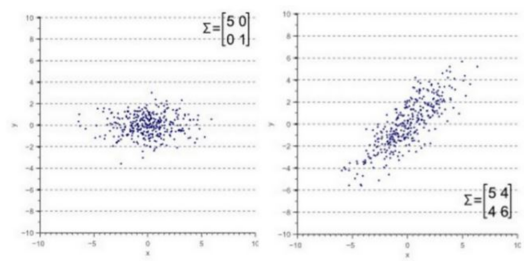

Fig. 2. Variance and Covariance

B. Eigenvectors and Eigenvalues

Eigen Vector is a vector whose direction is not changed upon applying a linear transformation as shown in Figure 3. Thus if A is the linear transformation matrix and $\vec{v}$ is a eigenvector, then $A\vec{v} = \vec{v}\prime$, where the transformed vector $\vec{v}\prime$ will be in the same direction as $\vec{v}$. However, the matrix A scales the vector $\vec{v}$.

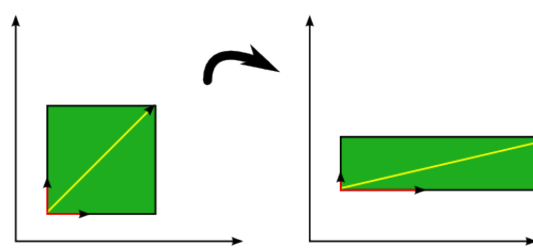

Fig. 3. Eigenvectors and Eigenvalues

Thus, the eigenvector $\vec{v}$ of the matrix A has the following relation,

$$A\vec{v} = \lambda\vec{v} \tag{1}$$

λ is called eigenvalue and it can completely define the linear transformation A of vector $\vec{v}$.

C. Decomposition of Covariance Matrix

A normal data distribution can be transformed to another normal distribution using a transformation matrix T which itself consists of a rotation matrix R and a scaling matrix S.

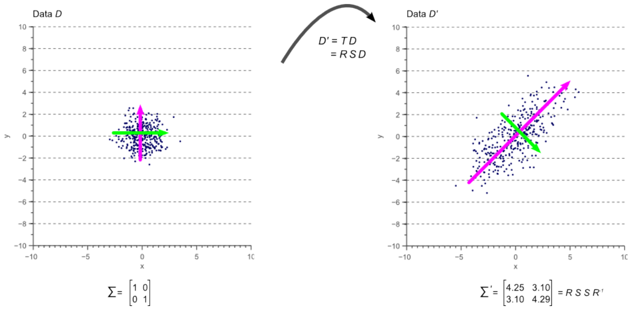

Fig. 4. (a) White Data (b) Transformed Data

If Σ represents the covariance matrix of the data D, then

$$\Sigma V = V L \tag{2}$$

Where V and L are the eigenvector and eigenvalue matrix of Σ respectively. By further solving the above equation gives the relationship,

$$\Sigma = R S S R^{-1} \tag{3}$$

where, $R = V$ and $S = \sqrt{L}$

III. Method

As mentioned previously, the main idea behind transferring the color behavior of one image to another image is modeling a covariance ellipse using statistical notions. On a high level, this approach moves the data points of the source image by scaling, rotating and then translating these points to the target image in RGB color space. Now for scaling the data points we need the mean values of both images. Similarly, for rotation, we need to calculate Eigenvector as we have already seen in equation (3) above, that eigenvector plays the role of Rotation matrix in Transformation T. Finally, we will calculate eigenvalues of both images for scaling as it represents magnitude in the direction of maximum variance.

The detailed steps of this algorithm are as followed:

1) We first calculate the mean $\mu_{\hat{src}}$, $\mu_{\hat{tgt}}$ and covariance Cov_{src}, Cov_{tgt} of source and target images respectively.
2) The second step involve decomposition of the Cov_{src}, Cov_{tgt} to get the eigenvectors used as rotation matrices and eigenvalues used as scaling matrices.
3) Now that we have the mean, rotation and scaling matrices of both images, we will first convert the target image to downscaled and uncorrelated data, also known as white data (shown in Fig. 4.a). This can be obtained by first translating the entire data to the mean, then aligning it with the axes to make it uncorrelated by rotating in opposite direction (U_{tgt}^{-1}). Finally downscaling this data by dividing it with the eigenvalue ($1/\sqrt{\lambda_{tgt}}$).
4) Following the above step, we get a downscaled and uncorrelated data which will now go through reverse steps, but using the source images transform matrices. This is performed by upscaling using the eigenvalues of source image ($\sqrt{\lambda_{src}}$), then rotation using eigenvector of source image (U_{tgt}) followed by translating using mean $\mu_{\hat{src}}$.

IV. Results

When we transfer color from source image to a target image, the target image takes look and feel of source image. This can be seen in Fig. 5, however this transfer is global. Now consider source and target images as shown in Fig. 6, as these two images has different color composition. In such cases, the global color transfer fails because of the characteristics of the images as source image has a very few features that can be matched with target. This problem, however, can be solved using swatch based approach. In swatch-based transfer, instead of transferring entire characteristics at once, we select different swatches to match in both images. This customization gives great results using the same statistics based transformations.

Fig. 5. Result-1

Fig. 6. Result-2

V. Conclusion

This approach is very intuitive and yields great results. Moreover, all transformations are done in RGB color space instead of $l\alpha\beta$ as in [2].

References

[1] Xuezhong Xiao and Lizhuang Ma, *Color transfer in correlated color space*, ACM international conference, 2006.

[2] Erik Reinhard, Michael Ashikhmin, Bruce Gooch, and Peter Shirley, *Color Transfer between Images*, IEEE Comput. Graph. Appl., 2001.

[3] http://www.visiondummy.com/2014/04/geometric-interpretation-covariance-matrix/