Review on Color Transfer Between Images

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Abstract— In this paper we have reviewed and analyzed different techniques for transferring color among images. We have reviewed various methods for color transfer between images like Histogram Matching (HM), Means and Variance, Color Category Based Approach, Gradient Preserving Model, N-dimensional Probability Density Function, Dominant Color Idea, Principal Component Analysis (PCA). For a purpose of smoothing of an image there are methods like EPS filter, JBF filter, Two Multiscale Schemes, Local Laplacian Pyramid available today. We have also represented analysis of these techniques in the form of table considering different factors like color effect, grain effect and details of image. It is concluded that some corruptive artifacts remains in these methods like color distortion, occurring noise, loss of details.

Keywords— Histogram matching, PCA, EPS filter, JBF filter, Image, Grain effect, Color effect.

INTRODUCTION

The availability of high dynamic range images increase due to advances in lighting simulation. Because of this there is an increasing demand to display these images more clearly. Every image has its individual color that significantly influences the sensitivity of human observer. Color manipulation is one of the most common tasks in image editing.

Color transfer between images is very applicable in various areas like photography, film industry, CCTV camera, medical, Hubble telescope, so on. For color transfer some automatic color transfer approaches developed and for edge preserving smoothing some filters are investigated for grain effect suppression and detail preservation but still they are not satisfying desired goals. Today's techniques develop methods to transfer color between images but it create some corruptive artifacts like color distortion, grain effect, loss of details. The need for adequate solutions is growing due to the increasing amount of digitally produced images in different areas as discussed earlier.

Ideally, color transfer between reference and target images should satisfy the goals like color fidelity, grain suppression, details preservation and enhancement.

Color fidelity: The color distribution of the target should be close to that of the reference image.
Grain suppression: No visual artifacts (grain/blocky artifacts) should be generated in the target image.
Details preservation: Details in the original target should be preserved after the transfer.

COLOR TRANSFER TECHNIQUES

1. Histogram Matching

The histogram of an image is a plot of the gray level values or the intensity values of a color channel versus the number of pixels at that value [1]. The shape of the histogram provides us with information about the nature of the image, or sub image if we are considering an object within the image. For example, a very narrow histogram implies a low contrast image, a histogram skewed toward the high end implies a bright image, and a histogram with two major peaks, called bimodal, an object that is in contrast with the background. The histogram features that we will consider are statistical based features, where the histogram is used as a model of the probability distribution of the intensity levels. These statistical features provide us with information about the characteristics of the intensity level distribution for the image.

The histogram matching is able to specify the shape of the referred histogram that we expect the target image to have. However, histogram matching can only process the color components of the color image. Since the relationship of the color components are separated.

Advantage:
Histogram matching is easy to calculate.

Limitation:
Histogram matching approach produces the unsatisfactory look, e.g. grain effect, color distortion.

2. Means and Variance

Reinhard et al. [2] firstly proposed a way to match the means and variances between the target and the reference image. The means and standard deviations are compute for each axis separately in correlated Lαβ color space.

Ruderman et al. developed a color space, called Lαβ, which minimizes channels correlation. Means and Variance contains mainly two steps:

2.1 Color space conversion

Reinhard first converted RGB color space into Lαβ color space.

(a) RGB To XYZ
This conversion depends on the phosphors of the supervise that the image was originally intended to be displayed on.

(b) XYZ To LMS
The data in this color space shows a great compact of skew, which can largely eliminate by transferring the data to logarithmic space.

$$L = \log L$$
$$M = \log M$$
$$S = \log S$$

(c) LMS ToLαβ
Thiscompute decorrelation between the three axes using principal components analysis (PCA). Assume the L channel as red, the M as green, and the S as blue, this is a variant of many opponent-color models.

Achromatic $r + g + b$
Yellow–blue $r + g - b$
Red–green $r - g$

2.2 Compute means and variance

Compute the means and standard deviations for each axis separately in Lαβ space.
Following steps are taken in this approach:
i) Subtract the mean from the data points.
ii) Scale the data points comprising the synthetic image by factors determined by the respective standard deviations. After this transformation, the resulting data points have standard deviations that will be conventional to the photograph. Finally, it converted the result back to RGB passing through log LMS, LMS, and XYZ color spaces.

Limitation:
The means and variance matching was produce slight grain effect and major color distortion.

3. Color Category Based Approach

To prevent from the grain effect, Chang et al. [3], [1] proposed a color category based approach that categorized each pixel as one of the basic categories. Then a convex hull was generated in Lαβ color space for each category of the pixel set, and the color transformation was applied with each pair of convex hull of the same category. Following steps conduct in this method as:

3.1. Handling the Illuminant Color in Images

First, apply the color-by-correlation method [9] to estimate the illuminant color. Each pixel color is transformed using the VonKries equation. The color-by-correlation method works well, but in case the estimation is not performed correctly.

3.2. Color Naming Method

Each pixel is categorized to BCCs(Basic Color Categories). The color naming method consists of two steps:
i) Initial color naming
ii) Fuzzy color naming

3.3 Compute Related Color Values in the Chromatic Categories

Basic convex hull is a convex hull that encloses all of the pixel color values within the basic color category. If the color distribution in the input image is smaller than that of the reference image, then the distribution keeps its original size. This guarantees that no pseudo contours will appear between pixels that belong to the same BCC (Basic Color Categories).

3.4 Compute Related Color Values in the Achromatic Categories

It separates the achromatic categories from chromatic categories. Because it is important that shadows or highlights of image remains same even after the color transformation. It separates the color transformations of achromatic pixels from the chromatic pixels. It balances the tones in the input and output images. It also deals with shadow or highlight regions for more accuracy.

3.5 Transferring Colors

The final equivalent color value of the pixel is computed by linearly interpolating the equivalent color values in each category. After this use the illuminant color of the reference image using the Von Kries equation.

Advantage:

Color Category-Based Approach was easily and quickly created a color transformed image or video.

Limitations:

The color-by-correlation method considered as an illuminant estimation method. If the numbers of surfaces are small, then the estimation ability is decrease.

4. Gradient Preserving Model

Xiao and Ma proposed a gradient-preserving model [6] to convert the transfer processing to an optimization, and balanced the color distribution and the detail performance.

A gradient mesh is a regularly connected 2D grid. The primal component of a gradient mesh is a Ferguson patch, which is determined by four nearby control points. Different from raster images, gradient meshes are defined in a parametric domain and have curvilinear grid structures. Based on gradient meshes, image objects are represented by one or more planar quad meshes, each forming a regularly connected grid. Every grid point has the position, color, and gradients. The image represented by gradient meshes is then determined by bicubic interpolation of these specified grid information. A grid point in a gradient mesh not only has color as a pixel does in an image, but also has color gradients defined in parametric domain.

In gradient preserving model, it used an extended PCA-based transfer to handle the color range, and propose a minimization scheme to generate color characteristics. These characteristics of source image are more similar to that of the reference image. Afterwards, a gradient-preserving algorithm is performed to suppress local color inconsistency. Finally, it develop a multi-swatch transfer scheme to provide more user control on color appearance.

Advantages:

Gradient preserving model maintain the grid structure of gradient meshes as well as achieve fast performance. By using fusion-based minimization scheme it improve the quality of the recolored gradient mesh. For flexible user control a multi-swatch color transfer scheme is developed.

Limitation:

Global optimal solution usually required large computational cost.

5. N-dimensional Probability Density Function

Pitié*et al.* [7], proposed an N-dimensional probability density function transfer approach to reduce the high-dimensional PDF matching problem to the one-dimensional PDF matching by Radon Transform[9]. This operation can reduce the color correlation and keep the color distribution of the transferred result consistent with that of the reference image. As the pixel intensity is changed it would lead to the change in the variance of image. Therefore, the Poisson reconstruction was introduced to medication the result.

In this method f(x) and g(y) are the pdf of X and Y, the original and target N-dimensional continuous random variables respectively. For example in color transfer, the samples x_i of X encapsulate the three color components $x_i = (r_i, g_i, b_i)$. The goal is to find a continuous mapping function t that transforms f in g.

Dimension:N = 1. This is a well known problem which offers a simple solution:

$$t(x) = C_Y^{-1}(C_X(x))$$

Where, C_X and C_Y are the cumulative pdfs of X and Y. This can be easily solved using discrete lookup tables.

Dimension: N ≥ 2**.** The idea is to reduce the problem from N dimensions to the 1-dimensional case. The projections of the N-dimensional samples for X and Y are computed along the axis. Matching these two marginal using the previous 1D pdf matching scheme results in a 1D mapping. This mapping can be applied along the axis to transform the original N-dimensional samples. The new distribution of the transformed original samples is proved to be actually closer to the target distribution than before transformation.

Advantages:
The pdf transfer operates in 1D so, the overall algorithm has a linear computational complexity of O(M),where M is the number of samples processed. It means that N-dimensional probability density function required low computation costs. If more bins are present in the histogram then this method achieve higher accuracy in the color mapping.

6. Dominant Color Idea

Dong et al. [8] proposed a dominant color idea for color transfer. When the amount of dominant colors of the target was consistent with that of the reference, the color of the reference would be transferred to obtain a satisfactory result.

Limitation:
When the amount of dominant colors was not balanced, the unsatisfactory result would be produced.

7. Principal Component Analysis (PCA)

Abadpour*et al.* [13] proposed the principal component analysis (PCA) and created a low correlated and independent color space to minimize color correlation.
The PCA approach is done as follows:
i) As per the given source image and the given reference image it create destination image. Firstly, both images are pass to the FPCAC. The results of the clustering are the two sets of membership maps. It describe the membership of each pixel in the source to that of each pixel of reference image. This is measured with respective to the cluster parameters. Here, the number of the clusters which should be input to the FPCAC.

ii) Now, using all the pixels in the reference image that belong to the some cluster, it produces the intermediate image. In fact, the set of artificial images make a pallet for the source image. In the same way the pallet for the reference image is produced.

iii) Now, for the color vector in the source image is a result image.

EDGE PRESERVING SOOTHING

The grain effect can be considered as a special type of noises, and it can be removed by linear smoothing. Even though the linear smoothing can remove the grains, the over-blurring destroys the original image details and decrease the sharpness of edges.

1. Edge Preserving Smoothing (EPS)

Edge-preserving smoothing (EPS) filters [9], are proposed to overcome the problem of over-blurring and low sharpness of edges. They can prevent the edge blurring by linear filtering according to their intensity or gradient-aware properties.

2. Joint Bilateral Filter (JBF)

Joint bilateral filter (JBF) [10], is the first guided edge-preserving smoothing method. The JBF exploits the pixel intensity of the reference which is correlated to the target to improve the filtering effect. This is a non-linear filter, where the weight of each pixel is computed using a Gaussian in the spatial domain multiplied by an influence function in the intensity domain that decreases the weight of pixels with large intensity differences.

Advantages
JBF preserve edges in smoothing process. It is a simple and intuitive. It is a non iterative method.

Limitations:
Like the bilateral filter (BLF), JBF cannot avoid the halo artifact and gradient reversal problem. This method does not preserve gradients.

3. Two Multiscale Scheme

Fattal et al. [11] proposed an elaborate scheme for details, but their adoptive bilateral decomposition has defects as aforementioned. Farbman et al. [12] proposed two multiscale schemes which are simpler than Fattals, because the WLS-based decomposition overcomes the defects of bilateral decomposition. Farbman et al. [13] introduced the diusion maps as a distance measurement to replace the Euclidean distance in their weighted least square filter.

Limitation
Two multiscale schemes create halo artifact.

4. Local Laplacian Pyramid

Paris et al. [14] explored the local Laplacian pyramid to yield the edge-preserving decomposition for fine-level detail manipulation.

5. Guided Filter

Guided filter derived from a local linear model. The guided filter generates the filtering output by considering the content of a guidance image. This guidance image can be the input image itself or different image. This filter can perform as an edge-preserving smoothing operator like the popular bilateral filter. This has better behavior near the edges. It also has a theoretical connection with the matting Laplacian matrix. It is a more generic concept than a smoothing operator and can better utilize the structures in the guidance image. This approach can be done by following ways:
(a) First define a general linear translation-variant filtering process. It includes a guidance image, an input image, and an output image.
(b) Now define the guided filter and its kernel.
i) The local linear model ensures that filter output has an edge only if input image has an edge.
ii) To determine the linear coefficients by minimizing the difference between filter output and the filter input.
iii) Find linear regression.
iv) Apply the linear model to all local windows in the whole image.

Advantages
The guided filter has a fast and non-approximate linear-time algorithm. Its computational complexity is independent of the filtering kernel size.

Limitations
Guided filter may create halo artifact near edge of image. As Guided filter is based on local operator, it is not directly applicable for sparse inputs like strokes.

ANALYSIS

Following table contains analysis of different color transfer methods between images:

Table 4.1: Analysis of different color transfer methods

Sr. No.	*Name of Method*	*Color Distortion*	*Grain Effect*	*Loss of Details*	*Computational Complexity*
1	Histogram Matching	Yes	Yes	Very Less	Very Low
2	Means and Variance	Yes	Less	Very Less	Very Low
3	Color Category-Based Approach	Yes	Very Less	Very Less	Low
4	Gradient Preserving Model	Very Less	Less	Very Less	High
5	N-dimensional probability density	Very Less	Very Less	Yes	Very Low
6	Dominant Color Idea	Yes	Very Less	Very Less	Low
7	Principal Component Analysis (PCA)	Very Less	Very Less	Very Less	High

CONCLUSION

In this paper, we have reviewed and analyzed different color transfer techniques. We observed thatHistogram Matching is easy to use but create unwanted result, Means and Variance avoid grain but create color distortion. Gradient Preserving Modeland Principal Component Analysis(PCA)are overall good methods but having large computational complexity. It is observed that color distortion artifact is common problem in most of the methods

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