Color Transfer Between Images By Minimizing Corruptive Artifacts

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Abstract: ***Color transfer between images is a critical operation in image editing but easily suffers from some corruptive artifacts in the mapping process. In this paper, a color transfer approach with corruptive artifacts suppression is define, which performs iterative probabilistic color mapping. It is done with the help of self-learning filtering scheme and multiscale detail manipulation scheme, which minimizes Kullback-Leibler distance. First, an iterative probabilistic color mapping is applied to construct the mapping relationship between the reference and target images. Then, a self learning filtering scheme is applied into the transfer process to prevent from artifacts and extract details. The transferred output and the extracted multi-levels details are integrated. This is done by the measurement minimization to yield the final result. This method achieves a sound grain suppression, color fidelity (the degree to which the output image matches the original images) and detail appearance.***

Keywords: Colored Image, Corruptive Artifacts, Grain, Color Fidelity.

1. Introduction

Color transfer between images is very applicable in various areas like Photography, CCTV camera, medical, Hubble telescope, so on. Today's techniques develop methods to transfer color between images but it create some corruptive artifacts like color distortion, grain effect, loss of details. Color handling is one of the most common tasks in image editing. Rapid development has been done in color transfer. Developed approaches include classical histogram matching, statistical transfer [2], N- dimensional probability density function transfer [3], gradient-preserving transfer [4], non rigid dense correspondence transfer [5], progressive transfer [6], and so on. Although many methods are effective in transferring the color information, they would create visual artifacts like:

Color distortion: Some disharmonious or unexpected colors appear which are not included in the reference image.

Grain effect: A phenomenon appears due to increase the noise level of the picture under the stretched mapping. Commonly, it looks like some noises or irregular blocks.

Loss of details: The details in the target image are missed after the color transfer process.

Figure 1: Techniques produce result but having some corruptive artifacts. [Source: Zhuo Su, Kun Zeng, Li Liu, Bo Li, and Xiaonan Luo,"Corruptive Artifacts Suppression for Example-based Color Transfer," IEEE Transaction on multimedia, VOL. 11, NO. 1, January 2013.]

In projected skeleton the method i.e. example-based color transfer present, which aims to achieve simultaneously grain suppression, color fidelity and detail preservation. Main approach is to incorporate a self-learning filtering scheme into the iterative probabilistic color mapping with minimizing K-L distance.

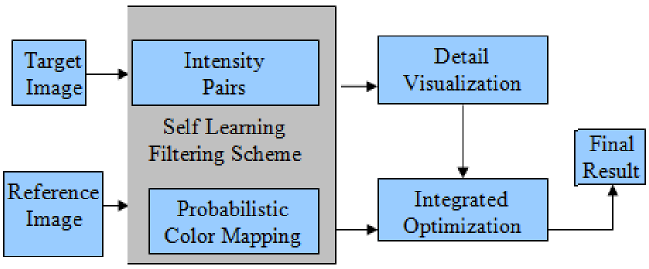


Figure 2: Flow of proposed system

First, a probabilistic mapping is iteratively applied to generate coarse color mapping. After this it reduce the N-dimensional probability distribution of both reference and target images to a one dimensional probability distribution pair. This method can match the color distribution of the target image to the reference image.

Second, the self-learning filtering method is used into the procedure of color mapping. The intensity channels are taken as the learning example for filtering. This can be achieve by converting target image into uncorrelated space, which is further applied to the mapped result.

2. Literature Survey

For color transfer some automatic color transfer approaches developed and for edge preserving smoothing some filters are used for grain effect suppression and detail preservation.

2.1 Color Transfer

2.1.1 Histogram matching

The histogram matching (specification) [7] 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.

Disadvantage

This approach produces the unsatisfactory look, e.g. grain effect, color distortion.

2.1.2 Means and Variance

Reinhard et al. [2] firstly proposed a way to match the means and variances between the target and the reference in the low correlated Lαβ color space. This approach was quite efficient.

Disadvantage

The simple means and variances matching were likely to produce slight grain effect and serious color distortion.

2.1.3 Color Category-Based Approach

To prevent from the grain effect, Chang et al. [8], [9] proposed a color category-based approach that categorized each pixel as one of the basic categories. Then a convex hull was generated in L__ 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.

2.1.4 Modified EM Algorithm

For the color distortion, Tai et al. [10] proposed a modified EM algorithm to segment probabilistically the input images and construct Gaussian Mixture Models (GMMs) for them, and the relationship was constructed by each Gaussian component pairs between the target and the reference under Reinhards approach [2].

2.1.5 Dominant Color Idea

Dong et al. [12] 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.

Disadvantage

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

2.1.6 Distribution-aware

Wu et al. [13] improved Dongs approach [12] and further proposed a distribution-aware conception to consider the spatial color distribution in the reference image.

2.1.7 Learning-based Color Transfer

Wang et al. [14], [15] developed the learning-based color transfer methods to train out the proper color mapping relationship.

2.1.8 Non-rigid Dense Correspondence

HaCohen et al. [5] presented the non-rigid dense correspondence and used it in example-based color transfer.

Disadvantage

The corresponding requirements are limit the example selection.

2.2 Edge-preserving Smoothing

The grain effect can be treated as a special type of noises [11], and it would be removed by linear smoothing. Although the linear smoothing can remove the grains, the over-blurring would destroy the original image details and lower the sharpness of edges.

2.2.1 Edge-preserving smoothing (EPS) filters

Edge-preserving smoothing (EPS) filters [16][18] are proposed to overcome this problem. They can prevent the edge blurring by linear filtering according to their intensity- or gradient-aware properties.

2.2.2 Joint bilateral filter (JBF)

Joint bilateral filter (JBF) [19], [20] is the first guided edge-preserving smoothing approach. The JBF exploits the pixel intensity of the reference which is correlated to the target to improve the filtering effect.

Disadvantage

Like the bilateral filter (BLF), JBF cannot avoid the halo artifact and gradient reversal problem.

2.2.3 Two Multiscale Schemes

Fattal et al. [33] proposed an elaborate scheme for details, but their adoptive bilateral decomposition has defects as aforementioned. Farbman et al. [17] proposed two multiscale schemes which are simpler than Fattals, because the WLS-based decomposition overcomes the defects of bilateral decomposition. Farbman et al. [21] introduced the di_usion maps as a distance measurement to replace the Euclidean distance in their weighted least square filter.

3. Problem Definition

Existing methods like Histogram matching, Means and variances, Dominant color idea, Modified EM algorithm, Principal component analysis but those methods do not give interactive manipulation. To minimize these issues novel method get developed.

Proposed method performs:
1) Iterative probabilistic mapping from reference to target image which removes color distortion.
2) Self-learning filtering minimize grain effect (noise).
3) Multiscale details manipulation preserves or enhances the details of image.

4. System Architecture

In the system of the color transfer between images, the self-learning filtering scheme is integrated into the probability based color distribution mapping to achieve triple functions, including color fidelity, grain suppression and detail manipulation

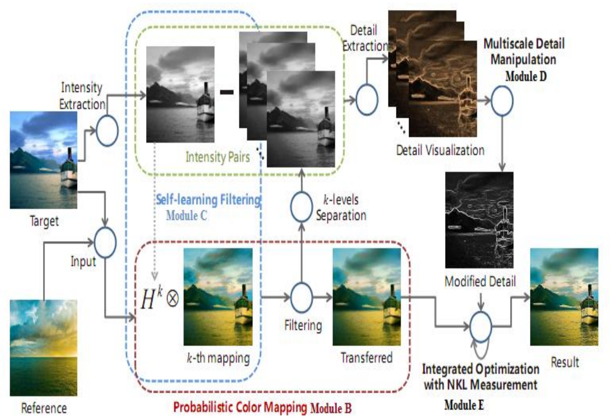


Figure 3: System Architecture:Color transfer between images by minimizing corruptive artifacts. [Source: Zhuo Su, Kun Zeng, Li Liu, Bo Li, and Xiaonan Luo,"Corruptive Artifacts Suppression for Example-based Color Transfer," IEEE Transaction on multimedia, VOL. 11, NO. 1, January 2013.]

A. Kullback-Leibler Distance for Color Transfer

The Kullback-Leibler distance (K-L) [13] can compute the similarity between two completely determined probability distributions. Here, it applies to measure the difference between the reference and transferred result in color transfer. The minimization of K-L distance means the color appearance of the target close to that of the reference. Let p(r) and p() denote the distributions of the reference image and the transferred image, respectively.

$$\min D_{KL}(\rho(g)\|\rho(r)) = \min \sum_j \rho_j(g) \ln \frac{\rho_j(g)}{\rho_j(r)} \quad (1)$$

K-L distance gives guarantee of the convergence of minimization.

In an iterative cycle, both images, the reference image and the target image are transformed into 2-D color vector pairs. As a result of the homography projection and probabilistic statistics with channel quantization, here obtain the 1-D distribution on directive axes. The probability distribution of the target image matches to that of the reference image. The restortion is performed to output the transferred result. The iterations are stop when it reaches the minimized error.

$$D_{KL}(\rho(g^{k+1}) \,\|\, \rho(r)) \le D_{KL}(\rho(g^{k}) \,\|\, \rho(r)) \quad (2)$$

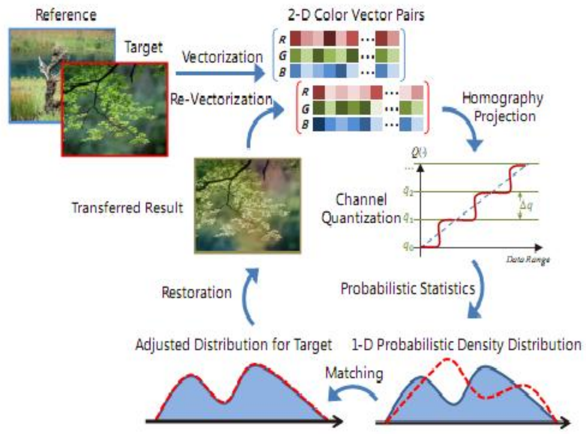


Figure 4: The probability based color distribution mapping with minimizing K-L distance. [Source: Zhuo Su, Kun Zeng, Li Liu, Bo Li, and Xiaonan Luo,"Corruptive Artifacts Suppression for Example-based Color Transfer," IEEE Transaction on multimedia, VOL. 11, NO. 1, January 2013.]

Where k is the iterative threshold. $D_{KL}(.)$ is a monotonically decreasing and positive function, therefore it has a limit. lim $D_{KL} = 0$, if the distribution ρ(g) and ρ(r) are equal. The above K-L distance is a fundamental measurement in proposed framework.

B. Iterative Probabilistic Color Mapping

For gray images, the probabilistic mapping relationship between both images (the reference image and the transferred image) formulated as,

$$\rho(g)dg = \rho(r)dr, \ \tau(g) = r \quad (3)$$

By creating the discrete look-up tables, solve the mapping relationship.

$$\tau = C_r^{-1} C g(g) \quad (4)$$

Where C_r and C_g denote the cumulative distribution corresponding to p(r) and p(g), respectively. However, due to the correlated property of color channels of colored image, direct matching in (4) is to produce color distortion. In proposed framework, exploit a decorrelation to remove this issue. This decorrelation means a piece-wise homography transformation with an iterative process. It is parameterized as the following

$$H = [I|R]^T \text{ X } Q_n \quad (5)$$

Where, I is a 3X3 identity matrix and R is a 3X3 homography coefficient matrix as a rotation projection. Q_n is a randomized orthogonal matrix used for n times iteration. In implementation, initially R = [2/3 2/3 -1/3; 2/3,-1/3 2/3;-1/3 2/3 2/3]. This setting can make the rotation satisfy the orthogonality. Afterward, a channel quantization with step Δq is used to control the scale of data range. This quantization gives the scale consistence in different date range. Then, the equivalent 1-D probability density distributions of both target and reference images are yielded by the probability statistics. This is similar to the image histogram. Following iterative method used result of transferred image:

$$g^{k+1} = g^k + H^T[\tau(Hg^k) - Hg^k] \quad (6)$$

The physical meaning of (6) could be interpreted as follows. The projection of 1-D probability density is obtained by homography transformation H, and the kth mapping result is calculated. Then, the difference between before and after mapping is evaluated by $\tau[(Hg^k) - Hg^k]$. The inverse transformation is used to restore the 2D image. Finally, the intermediate k is updated and a cycle of iteration is completed.

C. Self-learning Filtering Scheme

However, still there is a problem in the solution in iterative probabilistic color mapping method, that is, it is produce the grain effects sometimes. To reduce this challenging problem, a self-learning filtering scheme and iterative probabilistic color mapping is used. Firstly, assume the transferred result and its filtered output $\hat{g}$ are divided into a series of 9X9 patches, and each patch-pair has 1-to-1 corresponding relationship. Then, further assume that g and $\hat{g}$ have the following linear learning relationship in the patch p_k.

$$\hat{g}_i = \alpha_\kappa g_i + \beta_\kappa, \forall i \epsilon p_k \quad (7)$$

Where, α_κ and β_κ are linear coefficients. Subscripts i and k are used for pixels and patches indexing, respectively. Let μ_κ and σ_κ^2 be the mean and variance of g in p_k, |p| is the pixel amount of p_k. Using the least squares parameters estimation, α_κ and β_κ can be estimated by

$$\alpha_k = \frac{\frac{1}{|p|}\sum_{i\epsilon pk} g_i \hat{g}_i - \mu_k \overline{\hat{g}_k}}{\sigma_k^2}, \beta_\kappa = \overline{\hat{g}_k} - \alpha_\kappa \mu_\kappa \quad (8)$$

Where, $\overline{\hat{g}_k} = \frac{1}{|p|}\sum_{i\epsilon pk} \hat{g}_i$ However, $\hat{g}$ is an unknown variable. To determine α_κ and β_κ, we replace $\hat{g}$ by the target image. Then, (7) is reformulated as

$$\alpha_k = \frac{\frac{1}{|p|}\sum_{i\epsilon pk} g_i t_i - \mu_k \overline{t_k}}{\sigma_k^2 + \epsilon}, \beta_\kappa = \overline{t_k} - \alpha_\kappa \mu_\kappa \quad (9)$$

Where ϵ is used to compensate the error caused by the substitution. The self-learning filtering is an edge preserving smoothing operation under linear regression with reference image.

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

Figure 5: Self learning filtering scheme for grain suppression. [Source: Zhuo Su, Kun Zeng, Li Liu, Bo Li, and Xiaonan Luo,"Corruptive Artifacts Suppression for Example-based Color Transfer," IEEE Transaction on multimedia, VOL. 11, NO. 1, January 2013.]

D. Multiscale Detail Manipulation Scheme

As mentioned earlier, details in the original target image should be preserved after the transfer process. Details frequently associate to the style appearance. This characteristic is important to the color-related applications. Since proposed framework included the self-learning filtering scheme into the color mapping. This scheme can extract the details or enhancing them in the transferred output image. In this, k levels details dk are obtained by iteratively applying the self learning filtering scheme. The sigmoid function is used when the detail levels are considerably boosted. The multiscale detail manipulation scheme is formulated as,

$$M(d^k,\lambda) = \begin{cases} \frac{1}{k}\sum_i^k d^k, & \lambda = 1 \\ \sum_i^k \frac{1}{1+e^{-\lambda d^k}}, & \lambda \neq 1 \end{cases} \quad (10)$$

Where, λ is the adjustment factor for preserving (λ = 1) or enhancing ($\lambda \neq 1$) the details.

E. Integrated Optimization Framework

In Kullback-Leibler Distance method, represented the KL distance can be used to evaluate the similarity between the color distribution of the reference image and that of the transferred image. For more strong results, discussed framework prefer to use the normalized form instead

$$D_{NKL} = (D_{KL} - D_{KL}^{min})/(D_{KL}^{max} - D_{KL}^{min}) \quad (11)$$

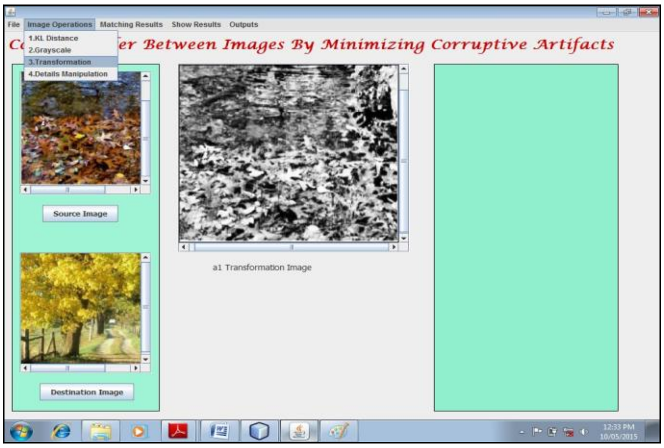
Then, according to methods A-D, summarize the color transfer framework with minimizing the normalized K-L distance in the following

$$minD_{NKL}(p(S(\hat{g},t) + M(d,\lambda))||p(r)) \quad (12)$$

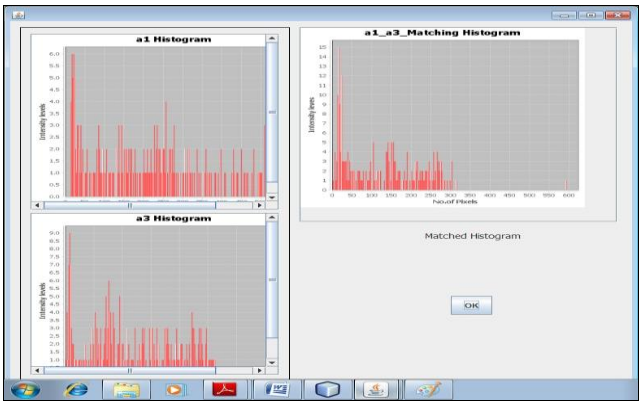
Where S(.) and M(.) denote the self-learning filtering operator and detail manipulation operator, respectively. With this a proposed unified framework, accomplish mentioned goals like grain suppression, color fidelity and detail preservation.

5. Results and Discussion

1. Source image and destination image or reference image are taken, after that performing grayscale and transformation operations:



2. Matched histograms of both images:



3. Details manipulation of source image for details enhancement:

4. KL Diatsnce (Kullback-Leibler Distance) between two images:

KLD sum = 0.7024765594763693

5. PDF (Probability Distribution Function) and CDF (Cummulative Distribution Function) values:

PDF of a1.jpg:
0 pdf 0.006360332294911735
1 pdf 0.0020443925233644858
.
.
.
255 pdf 0.0022066458982346834

CDF of a1.jpg:
0 cdf 1
1 cdf 2
.
.
.
255 cdf 254

6. Histogram levels:
Histogram levels of source image a1.jpg:
0 Histogram levels 222.0
1 Histogram levels 71.0
.
.
.
255 Histogram levels 594.0

Histogram levels of destination image a3.jpg:
0 Histogram levels 2.0
1 Histogram levels 7.0
.
.
.
255 Histogram levels 814.0

7. Matched PDF values:
PDF matching values:
0 Matched PDF's 4.861842638359938E-5
1 Matched PDF's 1.4585527915079814E-4
.
.
.
255 Matched PDF's 1.7826756340653108E-4

Final Result:

Source Image Reference Image

Final Color Transferred Image

6. Conclusion

The color transfer between images is very significant in various areas. It is a challenging task due to generation of corruptive artifacts like color distortion, grain effect, loss of details. The discussed framework minimizes these corruptive artifacts using a novel color transfer method. This method used self-learning filtering scheme and iterative probabilistic color mapping model. Planned method not only prevents the color distortion and grain effect in the process of color transfer, but also enhances the effect of detail preserving. It also supports to multiple-reference color transfer instead one-to-one color transfer.

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