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Example Based Color Transfer to Remove Corruptive Artifacts of Single and Multiple Reference Images

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Abstract: ***Color transfer is an important task in image editing. Among which example based color transfer is used for color transfer and also suppresses the corruptive artifacts during color transfer. In the example based color transfer there exist single or multiple example images as reference and a target image. Color transfer is the process of copying the color appearance of a target image based on reference. In this paper, a novel unified corruptive artifacts suppression color transfer frame work is introduced, which having iterative probabilistic color mapping with self-learning filtering scheme and multiscale detail manipulation scheme in minimizing the normalized kullback-leibler distance. This paper also proposes an automatic color transfer method for processing images with complex content based on intrinsic component. Visual artifacts and color bleeding like artifacts are removed in this paper.Intrinsic component is used for local organization and to remove color bleeding like artifact.***

Keywords: color transferring, computational photograph, edge preserving Smoothing, image detail manipulation,content-based image retrieval

1. Introduction

Image editing is the common task in image manipulation. The task of example-based color transfer [1] involves the changing color appearances based on the reference image and also transfers the original feel to the target. there exist sudden development in the field of color transfer, such that there exist many representative approaches exist they are , progressive transfer [6], non-rigid dense correspondence transfer [5]classical histogram matching, n -dimensional probability density function transfer [3] ,statistical transfer [2], gradient-preserving transfer [4] etc.

These approaches are good in color transfer but it makes some visual artifacts. Considering the fig. 1 we can understand that unsatisfactory results with artifact are obtained due to the big difference in intensity distribution of target and reference. The remarkable artifact can be listed below.

- *Loss of details:* after color transfer the finest details in the target image are missed.
- *Grain effect*: during stretched mapping enhancing the noise of an image takes place. Some irregular blocks or noises are similar to that of this phenomenon.
- *Color distortion:* some unwanted color appears, which are not in the reference image

2. Literature Survey

In this section state of art of the automatic color transfer is emphasized, and also summarizes its merits and de merits. Edge preserving smoothing filters, multiple references and multiple references with complex content are discussed.

- *Color fidelity*: the reference and target should have the close color distribution.
- *Detail preservation*. Details of the target should be preserved after color transfer.
- *Grain suppression:* target image should free from visual artifacts

Color transfers between two images are become efficient when they satisfy the following goals.

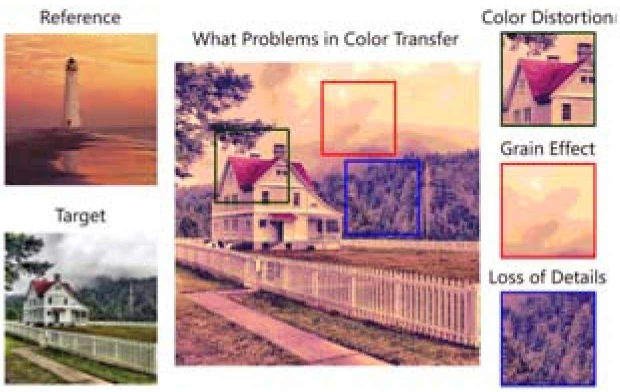

Figure 1: Example-based color transfer [7] is an intuitional image manipulation technique, but it would produce some unexpected artifacts due to the complexity of color mapping. Grain effect, color distortion and loss of details appear in the transferred result commonly.

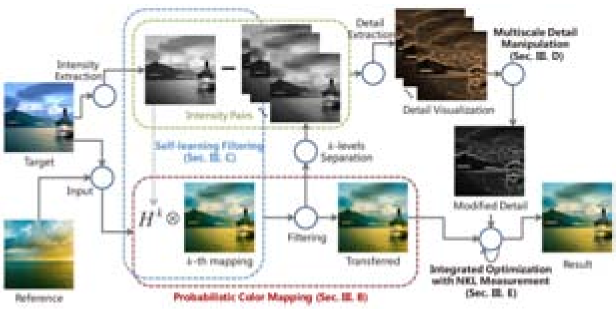

Figure 2: The pipeline of our framework. In the procedure of the color transfer, the self-learning filtering scheme is

integrated into the probability-based color distribution mapping to achieve triple functions, including color fidelity, grain suppression and detail manipulation. This integration has simple and efficient characteristics. We will demonstrate its effectiveness in the following sections and its applicability in lots of color-related applications.

A. Color mapping

Histogram matching [8] is the classical method in which the target histogram is obtained from the reference histogram. The color component of the color image is processed independently during histogram matching. Relationships of the color component are separated, such that unsatisfactory result with slight grain effect and serious color distortion are produced. The first method in color transfer is the Reinhard et al. [2],in which the low correlated lαβ color space is used as the color space such that the matches occurs between the mean and variances of the target and reference. Removing dominant and undesirable color cast occurred during color transfer and also the cross-channel artifacts are removed. Believable output images are produced after this method .it is the simple and efficient but two problems exist they are;

- Unnatural looking results when source and reference images have different color distributions
- Results with low fidelity in scene details and color distribution

The Chang et al. [9], [10]proposed a method to prevent from grain effect, it is a color category-based approach that categorized each pixel as one of the basic categories, then calculate a corresponding color value for each convex hull of the same category. This method quickly create a color transformed image or video using one reference image. It can handle images taken under a variety of light conditions and improves the mapping between source and reference colors when there is a disparity in size of the chromatic categories .it also handles achromatic categories separately from chromatic categories. This method produces color distortion. Tai et al. [11] proposed a method to avoid the color distortion by using EM algorithm, such that it construct GMM (Gaussian mixture model) with the help of Reinhard's approach [2].N-dimensional probability density function transfer approach by Pitié et al. [3],[12] uses radon transform [8] to reduce an N-dimensional PDF matching problem in to one dimension. Transfer the statistics of a target dataset (the example) to a source dataset. It having low computation cost but visual artifacts are produced such that the variance of image contents as the pixel intensity changed .to avoid this result Poisson reconstruction is introduced. Gradient-preserving model by Xiao and Ma [4] introduced fidelity both in terms of scene details and colors. Combine the gradients and a histogram for a gradient-preserving color transfer algorithm. Objective evaluation metric is used for example-based color transfer to measure the fidelity. It needs more computing resources including time and memory .It involves solving a huge scale linear system of equations.

B. Edge-Preserving Smoothing

The grain effect can be removed by linear smoothing because it is a special type of noise [12]. But the linear smoothing will produce over-blurring, which removes original image details, and the sharpness of the edges are reduced. Edge-preserving smoothing (EPS) filters [13]–[18] are proposed to avoid this problem. Fattal et al. [19] proposed an image- based technique for enhancing the shape and surface details of an object. It contains two phases such as analysis and synthesis phase. The shape and detail enhancement system is composed of two stages; analysis and synthesis. In the analysis stage we compute a multiscale decomposition for each input image and in the synthesis stage we combine information within each scale of the decomposition, but across all of the input images to generate the enhanced output image. Paris et al. [20] explored the edge-aware image processing based on the Laplacian pyramid for the decomposition for fine-level detail manipulation. It allows for a wide range of edge-aware filters and produce artifact-free images

C. Multiple References

Wan-chien chiou and chioting hsu[22] proposed an automatic color transfer method based on multi-reference and graph-theoretic region correspondence estimation. Content-based image retrieval technique is used to retrieve k set of reference images from the database. After that segment the target image using mean-shift based technique. Then represent each image as an attributed graph and derive a novel region mapping function as the criterion. Finally perform color transfer between the best-matched region pairs. This method produces color-bleeding like artifact. To remove this Wan-chien chiou, yi-lei chen and chiou-ting hsu [23] proposed a method based on intrinsic component. It incorporates the idea of intrinsic component to better characterize the local organization within an image and to reduce the color-bleeding artifact across complex regions. Using intrinsic information, first represent each image in region level and determine the best-matched reference region for each target region. Next, conduct the color transfer between the best-matched region pairs and perform weighted color transfer for pixels across complex regions in a de-correlated color space.

3. Proposed Method (Integrated Color Mapping Model)

In the example based color transfer the color transfer exist between the target and the reference image, such that it should satisfy the three goals of color transfer simultaneously, including grain suppression, detail preservation and color fidelity respectively. The overview of the frame work in Fig. 2 contains the following stages,

- *Color mapping stage:* this stage contains an iterative probabilistic mapping to provide basic color categories followed by self learning filtering scheme to remove the grain effect and produce k levels of transferred target.
- *Detail manipulation stage:* in this stage preserve or enhance details by using a multiscale detail manipulation scheme.
- *Integrated optimization stage:* to yield the final result the transferred and modified result are combined such that it will having a minimum K-L distance.

A. K-L distance for color transfer

The Kullback-Leibler distance (K-L) [21] can measure the similarity between two completely determined probability distributions. Here, we are using K-L distance to measure the difference between the reference r and the transferred result g during color transfer. The color distribution of target is close to that of the reference if there exist a minimum K-L distance. Let p(r) and p(g) denote the distributions of the reference image and the transferred image, respectively, we have

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

Taking the K-L distance as a measurement in an optimization procedure, to guarantee the convergence of minimization, we require Eq. (2) should satisfy the following constraint.

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

Where DKL(.) is the iterative threshold in the solution. Essentially, is a monotonically non-increasing and non-negative function, therefore it has a limit. ilmitDKL=0 , if the distribution p(r) and p(g) are equal. The K-L distance is having a vital role in the color mapping.

A. Iterative probabilistic color mapping

The probabilistic mapping between the reference and transferred grayscale image can be formulated as

$$\rho(g)dg = \rho(r)dr,\ \tau(g) = r. \tag{3}$$

By using discrete look up tables the mapping relationship can be solved as

$$\tau = C_r^{-1} C_g(g), \tag{4}$$

Where Cr and Cg denote the cumulative distribution correspondingto P(r) and P(g) , respectively.

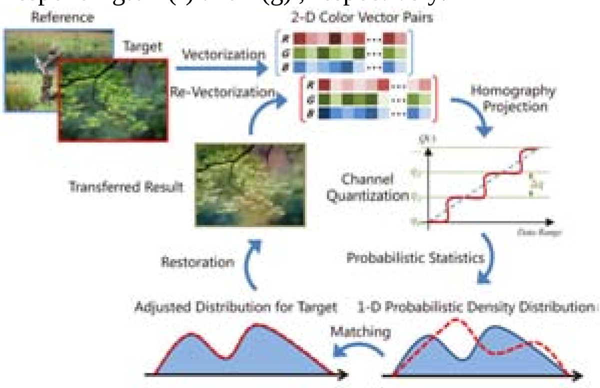

Figure 3: The probability-based color distribution mapping with minimizing K-L distance. In an iterative cycle, the reference image and the target image are transformed into 2-D color vector pairs. By the homography projection and probabilistic statistics with channel quantization, we obtain the 1-D distribution on directive axes. The probability distribution of the target matches to that of the reference. The restoration is performed to output the transferred result. The iteration would be stopped until reach the preset times or minimized error.

The above equation should produce color distortion in the case of color images. Decorrelation is used to solve this issue. This decorrelation would be regarded as a piece-wise homography transformation with an iterative process. It is parameterized as the projection with the randomized orthogonal transform in the following

$$\mathcal{H} = [I|\mathcal{R}]^{\mathbf{T}} \times Q_n, \tag{5}$$

Where I is a3×3 identity matrix and R is a homography coefficient matrix as a rotation projection.$Q_n$is a randomized orthogonal matrix used for n times iteration. The Fig. 3 explains the probabilistic color mapping. By the decorrelation, we use the following iterative scheme to solve out the transferred result

$$g^{k+1} = g^k + \mathcal{H}^{\mathbf{T}}\left[\tau\left(\mathcal{H}g^k\right) - \mathcal{H}g^k\right]. \tag{6}$$

B. Self-learning Filtering Scheme

After the probabilistic color mapping there still exist a defect of grain effect. To avoid this problem the self learning filtering scheme is introduced. The transferred result g and filtered result gˆ are divided into series of 9×9 patches such that g and gˆ having the following relationship in patchp_k

$$\hat{g}_i = \alpha_\kappa g_i + \beta_\kappa, \forall i \in p_\kappa, \tag{7}$$

Whereα_k and β_k are linear coefficients. Subscripts i and k are used for pixels and patches indexing, respectively. Let mean and variance of g in p_k is $\mu_k$andσk^2, |p|is the pixel amount of p_k. Using the least squares parameter estimation, $\alpha_k$and $\beta_k$can be estimated by

$$\alpha_\kappa = \frac{\frac{1}{|p|}\sum_{i\in p_\kappa} g_i\hat{g}_i - \mu_\kappa\overline{\hat{g}_\kappa}}{\sigma_\kappa^2},\ \beta_\kappa = \overline{\hat{g}_\kappa} - \alpha_\kappa\mu_\kappa, \tag{8}$$

We presented our result with this scheme and compared it with Pitiè's in Fig. 4 and Fig. 5. If it contains multiple reference images then this method will produce color-bleeding like artifact. To remove this replaces the equation for α and β by using [23]. If there exist multiple reference images, then current method produce colour bleeding like artifact, so take average of colour values of each reference image. By using this will gives a better colour appearance.

Figure 4: The comparison of the integrated color mapping model and Pitié's approach [14]. (a) Reference. (b) Target. (c) Pitié's -dimensional PDF step (n=10). There are obvious grain effect and content distortion in (c), e.g. the tone of the clouds. (d) Our improved result (k=8 ,ε=1e-3). We obtained a visual satisfactory result under the self-learning filtering

scheme. Furthermore, we compared the N-dimensional PDF added Poisson editing [14] in (e)-(f) with our approach in (g)-(h). (e) n=3,λ=1 . (f)n=10 ,λ=1 . (g)k=3 ,ε=1e-3. (h)k=10 ,ε=1e-3 .

C. Multiscale Detail Manipulation Scheme

After the color transfer the details in the target image should be preserved. Edge preserving decomposition is used to extract the details while compensating and enhancing of the transferred result. By applying self-learning filtering scheme iteratively it will produce k level details d^k .it can be formulated as

$$M(d^k,\lambda)=\begin{cases}\frac{1}{k}\sum_{i}^{k} d^k, & \lambda=1,\\ \sum_{i}^{k}\frac{1}{(1+e^{-\lambda d^k})}, & \lambda\neq 1,\end{cases} \tag{9}$$

Where λ is the adjustment factor, if λ=1 then it represent preserving, while λ≠1 represent the enhancing of details.The comparison of detail enhancement is shown in Fig. 6.

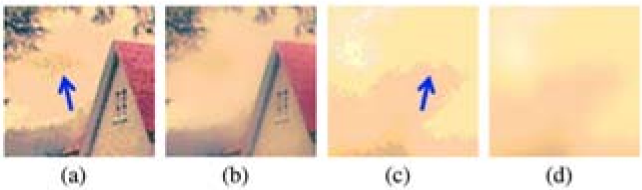

Figure 6: Self-learning filtering scheme for grain suppression. Note the grain effect can be smoothed while the edge can be preserved.

Figure 6: Detail enhancement. (a) Target. (b) Reference. (c) Without enhancing (λ=1). (d) Detail enhancing (λ=3). The specified magnified regions corresponding to (c) and (d) are shown in (e) and (f), respectively. Obviously, more details are presented in (f) than in (e).

E. Integrated Optimization Framework

The K-L distance can be used to evaluate the efficiency of color mapping. It represents the degree color distribution of similarity between the reference and the transferred result. Normalized K-L distance is used for more robustness.

$$D_{\mathrm{NKL}}=\left(D_{\mathrm{KL}}-D_{\mathrm{KL}}^{\min}\right)/\left(D_{\mathrm{KL}}^{\max}-D_{\mathrm{KL}}^{\min}\right). \tag{10}$$

The efficient color transfer will having a minimum of normalized K-L distance represented as the following equation.

$$\min D_{\mathrm{NKL}}\left(\rho\left(S(\hat{g},t)+M(d,\lambda)\right)\|\rho(r)\right), \tag{11}$$

Where S(.)and M(.) denote the detail manipulation operator and self-learning filtering operator , respectively. By using this framework it can produce a good result with the goals satisfied. The pseudo code of this approach is given in Algorithm 1.and results are presented in Fig. 4.

Algorithm 1: Integrated Color Mapping Model

Input: t: target image, r: reference image, k: iterative times, ε: regularization factor, λ: detail factor

Output: g: transferred result

```
g^0 = t, i = 0, δ = D_NKL(t, r) % Initialization
while i < k do
    while δ^i = D_NKL(g, r) ≥ δ^max do
        H = [I, R] * orth(rand(Q_n)) % Homography Transformation
        G = H^T g^i,  R = H^T r
        S_min = min(G, R),  S_max = max(G, R)
        S = (S_max − S_min)/q % q steps of quantization for G&R
        ρ(g^i) = Hist(S, G),  ρ(r) = Hist(S, R)
        τ = HistMatch(ρ(g^i), ρ(r)) % 1D distribution matching
        g^{i+1} = g^i + H[τ(G) − G] % Iterative update
        α = ((1/|p|) Σ t(g^{i+1}) − μ g^{i+1})/(σ^2 + ε)
        β = mean(g^{i+1}) − αμ
        ĝ = α * g^{i+1} + β % Apply self-learning filtering
        d = t − ĝ
        g^{i+1} = ĝ + M(d, λ) % Detail manipulation
    end while δ
end while k
return
```

4. Conclusion

In this paper, we propose a comparison of the performance of different methods and automatic color transfer method for processing images with single and multiple references. This paper introduces a new example based color transfer such that it removes the visual artifacts and satisfies the three goals including grain suppression, detail preservation and color fidelity. It also removes the color bleeding like artifacts.

References

[1] T. Welsh, M. Ashikhmin, and K. Mueller, "Transferring color to greyscale images," ACM Trans. Graph., vol. 21, no. 3, pp. 277–280, 2002.
[2] E. Reinhard, M. Ashikhmin, B. Gooch, and P. Shirley, "Color transfer between images," IEEE Comput. Graph. Applicat., vol. 21, no. 5, pp. 34–41, 2001.
[3] F. Pitié, A. C. Kokaram, and R. Dahyot, "N-dimensional probablility density function transfer and its application to colour transfer," in Proc. 10th IEEE Int. Conf. Computer Vision, 2005, vol. 2, pp. 1434–1439.
[4] X. Xiao and L. Ma, "Gradient-preserving color transfer," Comput. Graph. Forum, vol. 28, no. 7, pp. 1879–1886, 2009.
[5] Y. HaCohen, E. Shechtman, D. B. Goldman, and D. Lischinski, "Nonrigid dense correspondence with applications for image enhancement," ACM Trans. Graph., vol. 30, no. 4, pp. 70:1–70:10, 2011.
[6] T. Pouli and E. Reinhard, "Progressive color transfer for images of arbitrary dynamic range," Comput. Graph, vol. 35, no. 1, pp. 67–80, 2011.
[7] T. Pouli and E. Reinhard, "Example-based color image manipulation and enhancement," in Proc. ACM SIGGRAPH 2012Courses, ser. SIGGRAPH '12, 2012, pp. 3:1–3:62.
[8] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 3rd ed.Upper Saddle River, NJ, USA: Prentice Hall, 2008.
[9] Y. Chang, S. Saito, and M. Nakajima, "Example-based color transformation of image and video using basic color categories," IEEE Trans.Image Process., vol. 16, no. 2, pp. 329–336, 2007.
[10] Y. Chang, S. Saito, K. Uchikawa, and M. Nakajima, "Example-basedcolor stylization of images," ACM Trans. Appl. Percept., vol. 2, no. 3,pp. 322–345, 2005.
[11] Y. Tai, J. Jia, and C. Tang, "Soft color segmentation and its applications,"IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 9, pp.1520–1537, 2007.
[12] F. Pitié, A. Kokaram, and R. Dahyot, "Automated colour grading usingcolour distribution transfer," Comput. Vision Image Understand., vol.107, no. 1-2, pp. 123–137, 2007.
[13] S. Paris, P. Kornprobst, J. Tumblin, and F. Durand, "Bilateral filtering:Theory and application," in Proc. Computer Graphics and Vision 2008.
[14] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, "Edge-preservingdecompositions for multi-scale tone and detail manipulation," ACMTrans. Graph., vol. 27, no. 3, pp. 67–76, 2008.
[15] M. Kass and J. Solomon, "Smoothed local histogram filters," ACMTrans. Graphics (Proc. ACM SIGGRAPH 2010), vol. 29, no. 4, pp.100:1–100:10, 2010.
[16] E. S. L. Gastal andM.M. Oliveira, "Domain transform for edge-awareimage and video processing," ACM TOG, vol. 30, no. 4, 2011, Proc.SIGGRAPH 2011, to be published.
[17] L. Xu, C. Lu, Y. Xu, and J. Jia, "Image smoothing via l0 gradient minimization,"in Proc. SIGGRAPH Asia 2011, 2011.
[18] E. S. L. Gastal and M. M. Oliveira, "Adaptive manifolds for real-timehigh-dimensional filtering," ACM Trans. Graph., vol. 31, no. 4, pp.33:1–33:13, 2012.
[19] R. Fattal, M. Agrawala, and S. Rusinkiewicz, "Multiscale shape anddetail enhancement from multi-light image collections," ACM Trans.Graph., vol. 26, 2007.
[20] S. Paris, S. W. Hasinoff, and J. Kautz, "Local Laplacian filters:Edge-aware image processing with a Laplacian pyramid," ACM TransGraph., vol. 30, no. 4, pp. 1–12, 2011.
[21] C. M. Bishop, Pattern Recognition and Machine Learning. New York, NY, USA: Springer, 2006.
[22] W.C. Chiou and C.T. Hsu, "Region-Based Color Transfer from Multi- Reference with Graph-Theoretic Correspondence Estimation," Proc. ICIP, 2009.
[23] Wan-Chien Chiou, Yi-Lei Chen and Chiou-Ting Hsu," Color Transfer for Complex Content Images Based on Intrinsic Component," Department of Computer Science, National Tsing Hua University, Taiwan.2010

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