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.

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

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.

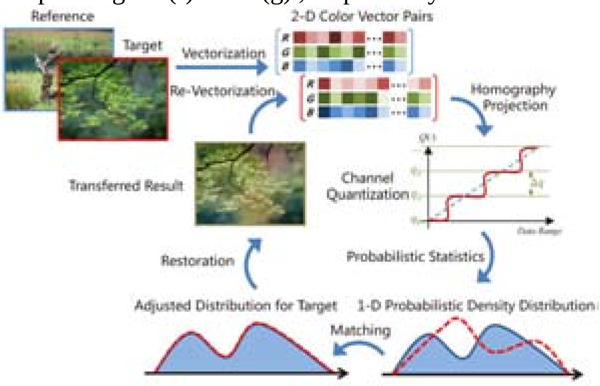

Figure 3: The probability-based color distribution mapping with minimizing K-L distance. In an iterative cycle, the reference image and the target image are transformed into 2-D color vector pairs. By the homography projection and probabilistic statistics with channel quantization, we obtain the 1-D 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.

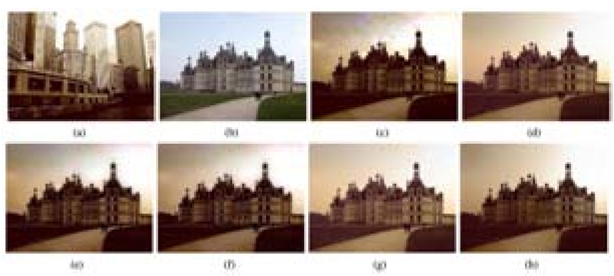

Figure 4: The comparison of the integrated color mapping model and Pitié's approach [14]. (a) Reference. (b) Target. (c) Pitié's -dimensional PDF step (n=10). There are obvious grain effect and content distortion in (c), e.g. the tone of the clouds. (d) Our improved result (k=8 ,ε=1e-3). We obtained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

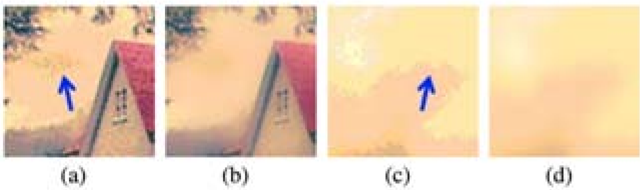

Figure 6: Self-learning filtering scheme for grain suppression. Note the grain effect can be smoothed while the edge can be preserved.

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

$g^0=t,\ i=0,\ \delta=D_{\mathrm{NKL}}(t,r)$ % Initialization
while $i<k$ **do**
  while $\delta^i=D_{\mathrm{NKL}}(g,r)\geq\delta^{\max}$ **do**
    $\mathcal{H}=[I,\mathcal{R}]*orth(rand(Q_n))$ % Homography Transformation
    $G=\mathcal{H}^{\mathbf{T}}g^i,\ R=\mathcal{H}^{\mathbf{T}}r$
    $S_{\min}=\min(G,R),\ S_{\max}=\max(G,R)$
    $S=(S_{\max}-S_{\min})/q$ % q steps of quantization for $G\&R$
    $\rho(g^i)=\mathrm{Hist}(S,G),\ \rho(r)=\mathrm{Hist}(S,R)$
    $\tau=\mathrm{HistMatch}(\rho(g^i),\rho(r))$ % 1D distribution matching
    $g^{i+1}=g^i+\mathcal{H}[\tau(G)-G]$ % Iterative update
    $\alpha=(\frac{1}{|p|}\sum t(g^{i+1})-\mu g^{i+1})/(\sigma^2+\varepsilon)$
    $\beta=\overline{g^{i+1}}-\alpha\mu$
    $\hat{g}=\alpha*g^{i+1}+\beta$ % Apply self-learning filtering
    $d=t-\hat{g}$
    $g^{i+1}=\hat{g}+M(d,\lambda)$ % 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.

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