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Smooth Context based Color Transfer

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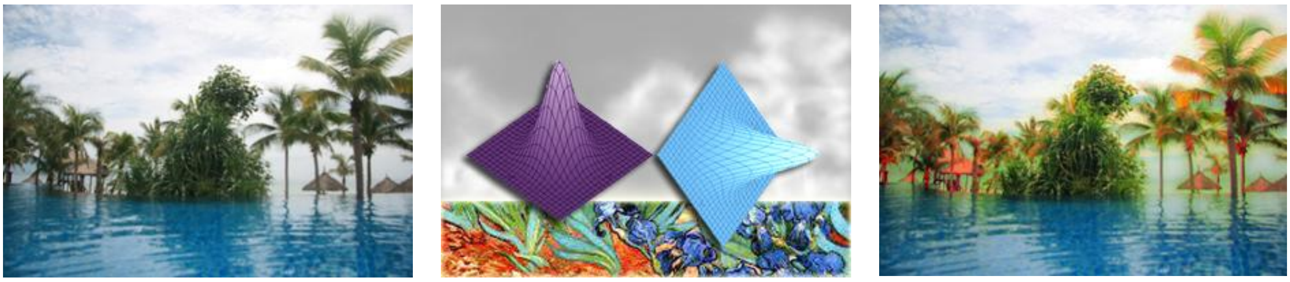


a. Input image b. Smooth context by bilateral filter on top,and target color at the bottom c. Result, SSIM=0.9998, t=4.05

Figure 1:Color transfer in smooth context

ABSTRACT
Color transfer is an emerging framework for dealing with ubiquitous color manipulation in media such as documents and images. Despite the notable progress made in the field, there remains a need for designers that can represent the same information in personalization and corresponding to media context. This work presents adaptive color transfer method using cross-disciplinary interaction of semantic context and bilateral filters. Colors in the method are transferred softly in matching with saliency distributed context. Preliminary results show that the framework is highly keeping consistency and promising. Consequently in this work, a solution of tone mapping by color transfer is introduced. Experimental results are further showed pertaining for automatic handling colors and contrast.

General Terms
Pattern Recognition, Algorithms

Keywords
Context, smooth, color transfer, bilateral filter, saliency, tone mapping

1. INTRODUCTION
As digital camera technology has advanced in the past decade, colors manipulation, and color transfer in particular is still fundamental and strong basics for several image analysis applications. The term color transfer is used here specifically to the transferring the color style from the target image to the source image.

Reinhard et al in [1] provides a comprehensive overview of simple solution to impose one image's color characteristics on another, where color correction is achieved by choosing an appropriate source image and applying its characteristic to another image. The use of statistical analysis can greatly simplify the computational load of learning colors, provided it can be successfully matched and optimized for the problem at hand. Recent works by [2], [3], [4], [5] have made great strides in scaling both automatic and custom-handled color transfer, though context consistency of these models remains unremarkable.

In addition, recent saliency findings suggest that salient regions should contain not only the prominent objects but also the parts of the background that convey the context [6]. Such salient regions facilitate effective matching and interpretation of visual information, particularly in the context of capturing spatio-color dependencies.

In fact, if a stimulus is insufficiently salient, sky and water in a scene as in Fig.1a are not changed in color transfer result as in Fig.1c. In this case, saliency map displayed in upper part ofFig.1b is fairly reasonable. Target color as in bottom part asofFig.1b is applied mainly to foreground by the saliency map. The map is smooth but it keeps major features by bilateral filter [9]. The result looks more natural with new color transferred into foreground while keeping background mostly the same. Structural similarity (SSIM) index [7] is 0.9998 for the case.

This work has several technical contributions. Firstly, new algorithm of Smooth Context Based Color Transfer (SCCT) is proposed and analyzed. This is a development of statistics-based method [8] for color distribution transfer. The method used different color distribution to find mapping relations for color transfer. This method now is combined with context-aware saliency [6] and bilateral filter [9] in our work to produce a new way of color transfer. Secondly, a solution for tone mapping is suggested. This is the practical implementation the SCCT algorithm for high dynamic range images. Though the solution is not fully automatic but it's simple, effective and can produce creative results in artistic styles following artist's reference.

2. OUTLINE OF PAPER
In the following sections core concepts are reviewed pertaining to the smooth context based color transfer. The main color transfer mechanisms are discussed along with key metrics and parameters for formulating those mechanisms. Then the experiments are discussed for the McGill Calibrated Color Image Database [10] and results of using SCCT as a solution for the color transfer are demonstrated. High dynamic range images [11] then are tested with tone mapping solution by SCCT. Finally, the article is concluded with discussion and summary of projected future directions for our work.

3. PRIOR WORK
On the part to follow the article goals and approach it is helpful to review shortly some major color transfer methods. The task of color transfer still get a lot of attention since handling colors is essential in image analysis. Therefore, in

the last decades, a lot of work has been focused on the problem of color transfer.

Reinhard et al. [1] raised interest on color transfer by introducing the use of statistical analysis for transfer color between images. The mean and variance of colors in axes *lαβ* in the CIELAB color space are imposed in matching metrics. The operation is simple and effective, though it produces slight grain effect. Histogram [12] matching is also simple and fast method. As it does not check continuity of colors between neighborhoods pixels, results may have color distortion.

Another approach is to reduce the high-dimensional Probability Density Function (PDF) matching problem to the one-dimensional PDF matching by Radon Transform[13]in solving N-dimensional PDF for transfer [2], [8]. This method is a non-parametric and it requires low computation costs for matching arbitrary distributions. Color correlation is reduced. This work develops the approach in next section.

Work in [4] proposed gradient-preserving model that consider both color distribution and the scene details. An extended Principal Component Analysis (PCA) based transfer is used to manage the color range, and a minimization scheme is the base to generate color features. Optimal solution of the method requires large computational cost though it preserves the grid structure of gradient meshes.

Remote sensing image fusion using non-separable wavelet frame transform is a solution in [14] for the case, where it fuses high spatial resolution panchromatic image and low spatial resolution multispectral image of the same scene.

Recently, transfer color in 3D space [15] is proposed with scattered point interpolation scheme using moving least squares and strengthen it with a probabilistic modeling. The model can deal with mis-alignments and noise.

Color transfer can be performed by a dominant color idea [3]. The method produces good results when there is consistence between the amount of dominant colors of the target and that of the reference. color distortion may have place when the amount of dominant colors are not balanced.

Visual saliency is a profound challenge for detection of the salient regions of an image. The saliency factor estimated for regions is fairly benefit for object co-segmentation [16], classification [17], retrieval [18] and object tracking [19]. A solution of color transfer by the mean and variance of colors [1] is enforced with saliency map in [20].

Bilateral filter proposed by Tomasi and Manduchi [9] is non-iterative, stable and simple method. It takes into account both space and intensity difference from the central pixel to cut off the noise and avoid edges diffusing. The filter is applied to saliency map in our work.

Color transferis crucial for multimedia applications, starting from color correction. Selective color from reference image can be transferred to region where color is distorted [21]. Image in painting is a special case applicable by color transfer where all information including structure data in some regions is lost.

Stylizing images by manipulating color and contrast is the application addressed in [5]. Photos styles are managed by their associated key words and their colors can be changed by styles for consistency with context key words.

Learning abstract categories on color palettes can be used in the application of color transfer, personalization and image re-ranking [14]. The work suggests to consider combinations of colors or color palettes instead of a single color to learn categorization models.

Contrast transfer is another application of color transfer where pure and high contrast can be replaced by selected color contrast predefined in reference image. In some cases tone mapping can be seen like contrast transfer and it is solved by color transfer. Section 5 of this work presents application of our color transfer algorithm for tone mapping.

4. CONTEXT-BASED FILTER

Denote foreground by Ω_f and background by Ω_b for color image *u(x)*:

$$u(x):\Omega \to \Re^3 \tag{1}$$

$$\Omega = \Omega_f \cup \Omega_b, \Omega_f \cup \Omega_b = \varnothing \tag{2}$$

Working in the CIE Lab color space[26] is suggested for saliency detection as the Lab is designed to approximate human vision.

Convert RGB to Lab, and back functions:

$$u_{RGB}(x) \to u_{Lab}(x) \tag{3}$$

$$u_{Lab}(x) \to u_{RGB}(x) \tag{4}$$

4.1 Saliency Map

Saliency detection creates saliency maps*s(x)* and define Ω_f, Ω_b:

$$s(x):\Omega_f \to \Re^1 \tag{5}$$

$$\Omega_f = \{x, s(x) > \tau\}, \Omega_b = \Omega / \Omega_f \tag{6}$$

According to context aware saliency[6], patch *p(x)* is defined by pixel *x* and its surrounding patch, which gives an immediate local context. Let's recall distance between two patches:

$$d(p(x), p(y)) = \frac{d_{color}(p(x), p(y))}{1 + c(x) * d_{position}(p(x), p(y))} \tag{7}$$

where d_{color} and $d_{position}$ are Euclidean distance between the color/positions of patches *p(x)* and *p(y)*.

Context evaluation *c(x)*depends on *s(x)*:

$$c(x) = \lambda . s(x) \tag{8}$$

4.2 Bilateral Filter

Bilateral filter [9]that ignores a part of details and keeps major edges is applied to context *c(x)* to prevent color distortion and grain effect:

$$b(\mathrm{x}) = \frac{1}{W_{\mathrm{x}}} \sum_{\mathrm{y} \in S} G_{\sigma_s}(\| \mathrm{x} - \mathrm{y} \|) G_{\sigma_r}(\| c(\mathrm{x}) - c(\mathrm{y}) \|) c(\mathrm{y}) \tag{9}$$

Filter scales of the spatial σ_s and intensity σ_r manage the smooth effect of the filter.

4.3 Color Transfer

Input image *u(x)* and reference image *r(x)* have their sets of color samples. The distribution transfer problem [2] is to find a differentiable mapping *t* that transforms the original color PDF *f(u(x))* into a new color PDF *g(y(x))* that matches the reference PDF *g(r(x))*:

$$\int^{u} f(u)du = \int^{t(u)} g(y)dv \tag{10}$$

The Kullback–Leibler (KL) divergence [22] is used as a measure to quantify the level of matching transformed distribution $f^{(k)}$:

$$D_{KL}(f \parallel g) = \int_{u} f(u)\ln\left(\frac{f(u)}{g(u)}\right)du \tag{11}$$

Having full color transferred *y(x)* by (10), (11) [2], context-based color transfer for foreground Ω_f is done by the following regulation:

$$v(x) = b(x).y(x) + (1 - b(x)).u(x) \tag{12}$$

To transfer color with context *b(x)* for background Ω_b:

$$v(x) = (1 - b(x)).y(x) + b(x).u(x) \tag{13}$$

Now algorithm can be formulated as follows.

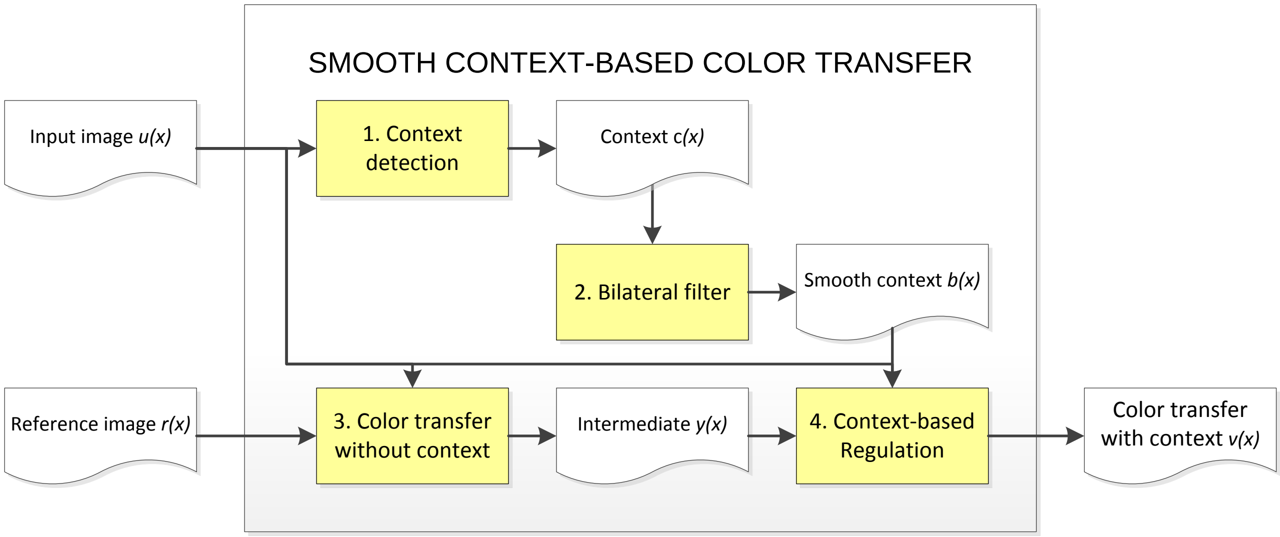
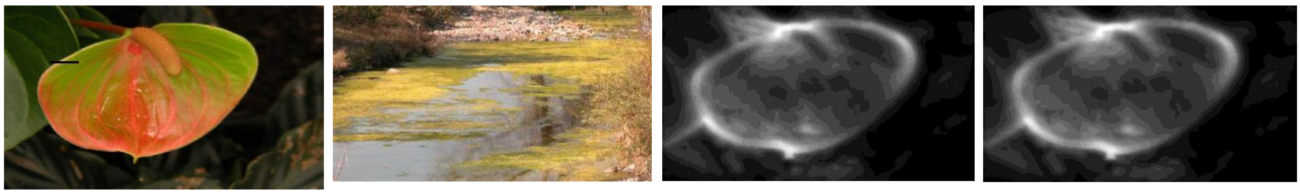
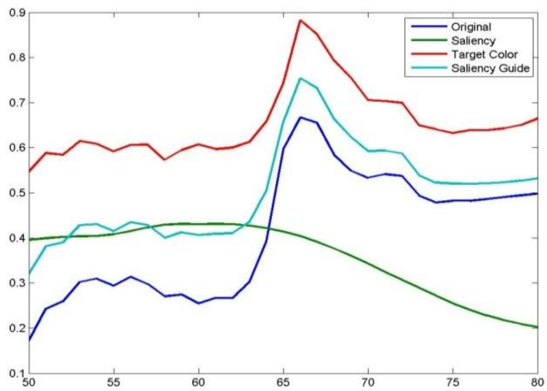


Figure 2:Algorithm of smooth context-based color transfer



a) Originalmerry0006.jpg **b)Reference color** **c)Saliency based context** **d)Smooth context**



e) Transfer without context, SSIM=0.9868, t=3.28

f) Graph of signals

g) Transfer for bacground with context, SSIM=0.9911, t=3.28

h) Transfer for foreground with context, SSIM=0.9991, t=3.28

Figure 3: Example of smooth context-based color transfer

4.4 Algorithm

The algorithm SCCT is short for “Smooth Context-based Color Transfer”. It contains the following steps.

Start: given an input image *u(x)* and reference image *r(x)*.

Use (3) to present *u(x)*and *r(x)* in Lab.

1.Context detection: defines saliency context *c(x)* by (7) and (8)[6].

2.Bilateral filter: makes context smooth *b(x)*by(9) [9].

3.Transfer without context: transfer full color schema to get *y(x)* by (10) and (11)[2].

4.Context-based regulation: regulates color transfer proportion by content-related weights *c(x)*to find*v(x)*by (12) and (13) for foreground and background accordingly.

Use (4) to get *v(x)* in RGB.

Figure 2 illustrates four steps of the algorithm by 4 blocks.

5. EXPERIMENTS

5.1 EXAMPLES OF SCCT

An example is displayed in figure 3: Input color image *u(x)* (fig.3a) from [10]needs to have new color transferred from reference image *r(x)* (fig.3b). Step 1 of the SCCT produced saliency based context *c(x)* in fig.3c. After step 2 we have smooth context *b(x)* in fig.3d. Using step 3, full color transferred version *y(x)* is shown in fig.3e. Finally, step 4 produces two versions *v(x)* for foreground (fig.3g) and background (fig.3h).Fig.3f draws original signal *u(x)*, saliency *s(x)*, target color *r(x)* and saliency guided context *c(x)* according to a black line in top left of fig.3a. The saliency guided context is smooth by the bilateral filter.

Each output image is shown with its SSIM index and run time in sec. Some other examples from [10] for foreground transfer are shown in Fig.5. Competitive high level of SSIM index for the examples strongly demonstrated benefits of context in handling color transfer: Result images keep well structure similar to their inputs. Statistics on SSIM average for examples from [10] show that both results with context on foreground and background have SSIM better than color transfer without context, see Fig.4. Background usually has largest space so applying context for them produces the best SSIM index.

Reference images from [24] are selected for visual view with our result as in Fig.6 to show results of other color transfer methods: separable linear transfer, Cholesky based transfer and linear Monge Kantorovitch transfer.

5.2 Tone Mapping

For completeness, in this experimental section the SCCT is tested with some tone mapping examples in Fig.8 from [11]. A part of each image is selected to make reference image for the SCCT algorithm. The parts should have harmonic contrast, so the contrast [25] can be transferred to result with harmonic contrast too. Though this solution is manual in the way of choosing reference image, it supports creative design for new look of media. Fig.7 shows tone mapping from [27], [28], [29] and SCCT for the same input. SCCT gives tone mapping result and keep well image structure with SSIM=1.

6. DISCUSSION

From the results reported for different image types we conclude that the SCCT method gives promising way for color transfer keeping initial context and saliency. Intuitively, using context information makes solution easier. In our method, preferable saliency detection method is context aware [2]. The saliency map played context role for color transfer. Bilateral filter makes context smooth to avoid color distortion and grain effect. The filter contains intensive filter with deviation σ_r to keep closely with local intensive change - the context condition in other words. So our solution is consistent and totally context-based.

7. FUTURE WORK

As future work, a new application of color transfer integrated with other features can get attention for improvement of the computer vision task.

8. CONCLUSION

A novel method for color transfer is presented. The main contribution is to show that the saliency based context significantly improves on existing methods. The saliency detection is included in the method to generate context for handling transfer process. Imposing this saliency in practices could make color transfer more comfortable with specific applications. Several examples, including tone mapping were shown with high level of accuracy and they demonstrated efficacy and usefulness of the method.

9. ACKNOWLEDGMENTS

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Color transfer	SSIM
IDT, no context [02]	0.9952
Context on foreground	0.9968
Context on background	0.9996

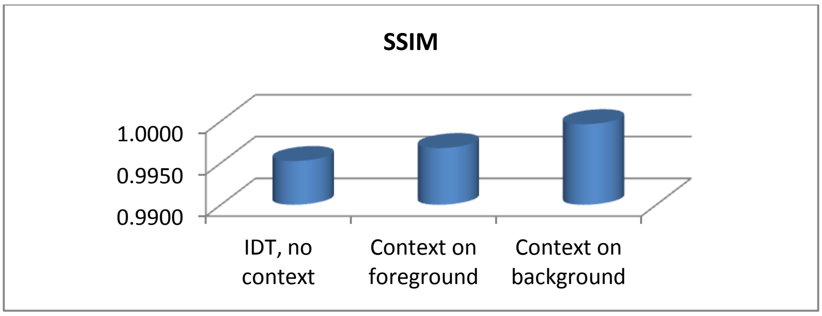
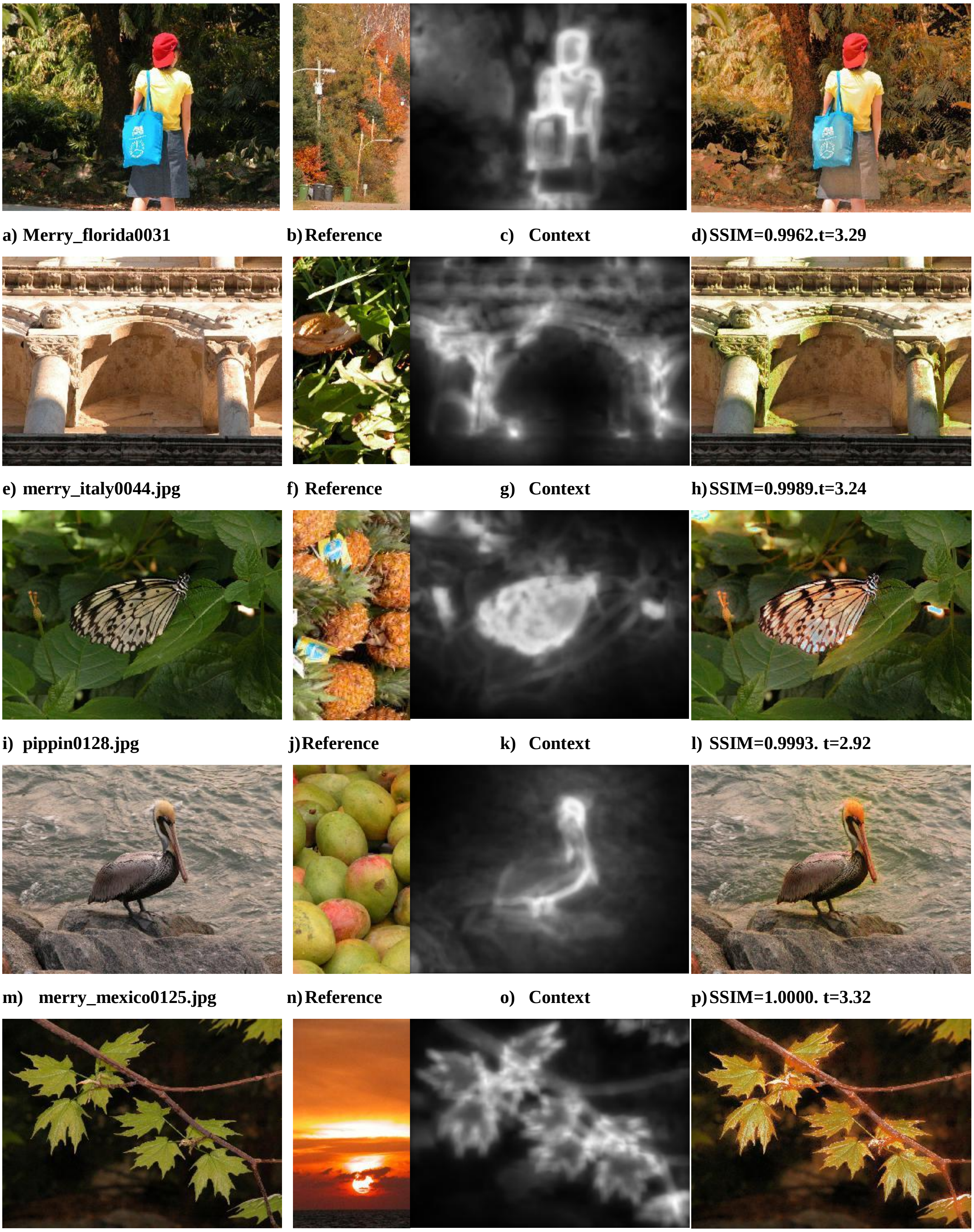


Figure 4: Statistics on SSIM average for examples from [10]



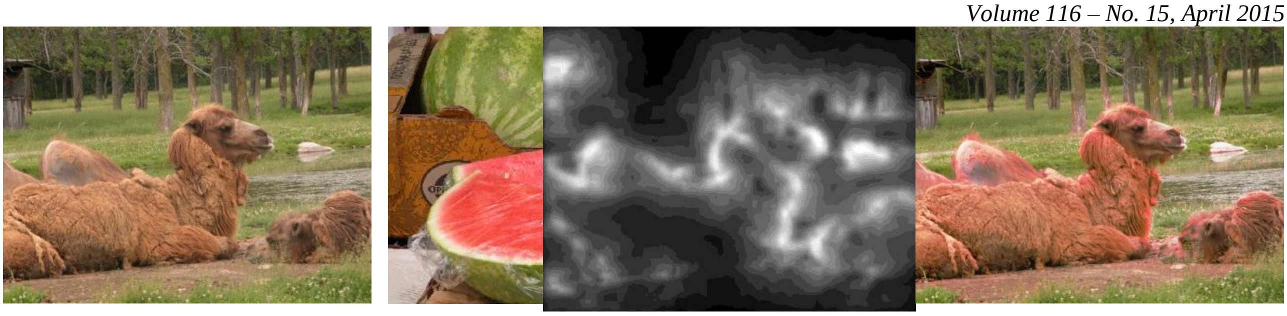
a) Merry_florida0031 b) Reference c) Context d) SSIM=0.9962.t=3.29

e) merry_italy0044.jpg f) Reference g) Context h) SSIM=0.9989.t=3.24

i) pippin0128.jpg j) Reference k) Context l) SSIM=0.9993. t=2.92

m) merry_mexico0125.jpg n) Reference o) Context p) SSIM=1.0000. t=3.32

q) pippin0096.jpg r) Reference s) Context t) SSIM=0.9990. t=3.16



u) pippin0021.jpg v) Reference w) Context x) SSIM=0.9999. t=3.30

Figure 5: Examples of smooth context-based color transfer for color images

a) Input b) Reference c) Separable linear transfer

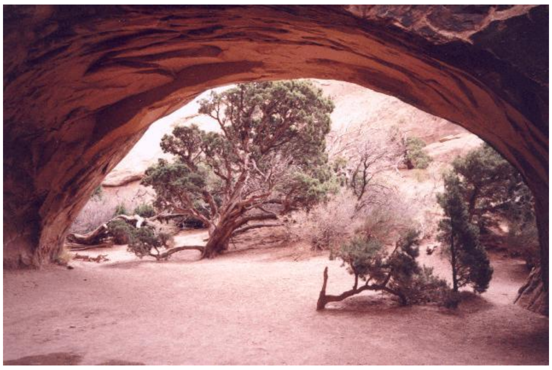
d) Cholesky based transfer e) Linear Monge-Kantorovitch transfer[24] f) SCCT, foreground

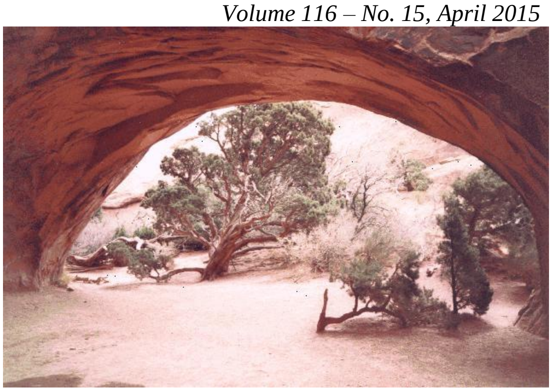
Figure 6: Examples of other color transfermethods

a) input b) Meylan et al [1], SSIM=0.9971 c) Shan et al [28], SSIM=0.9979

d) Yu-Jui Lin et al [29], SSIM=0.9927 e) Reference image f) SCCT with reference e), SSIM=1.

Figure 7: Examples of tone mapping from [28], [29] and [30] and SCCT

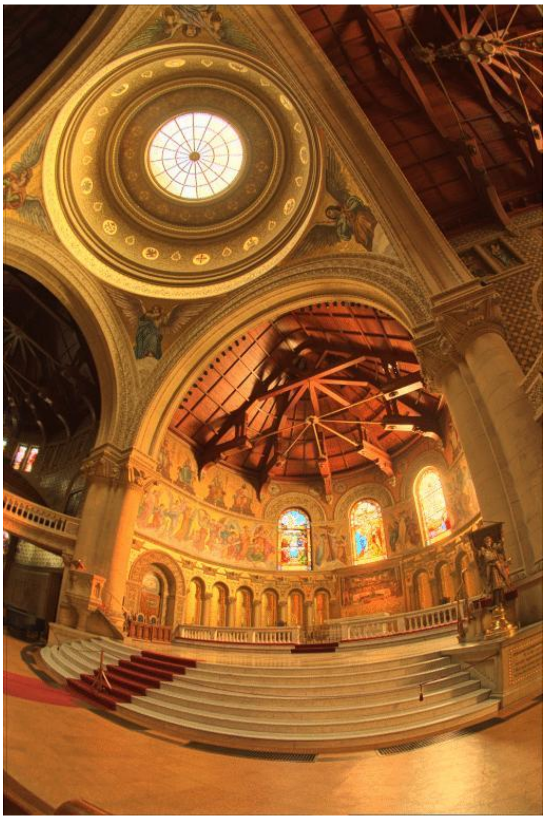


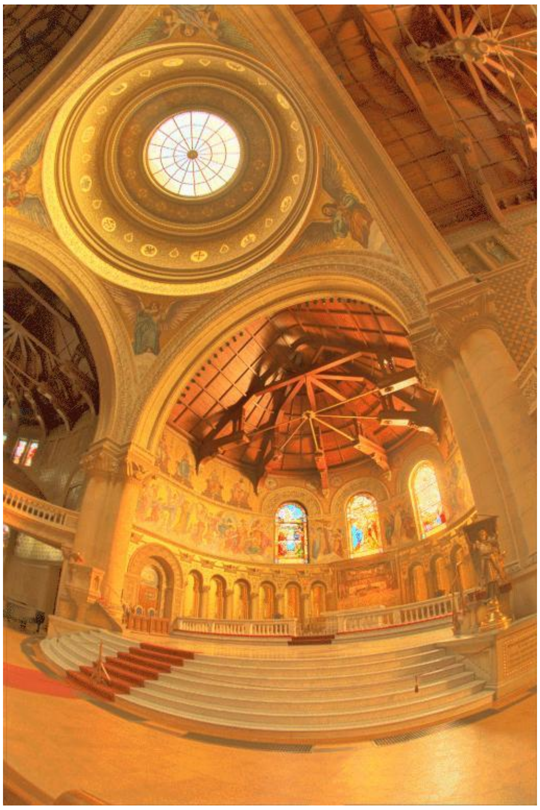


a) Arch.jpg **b) Reference** **c) SSIM=0.9989**

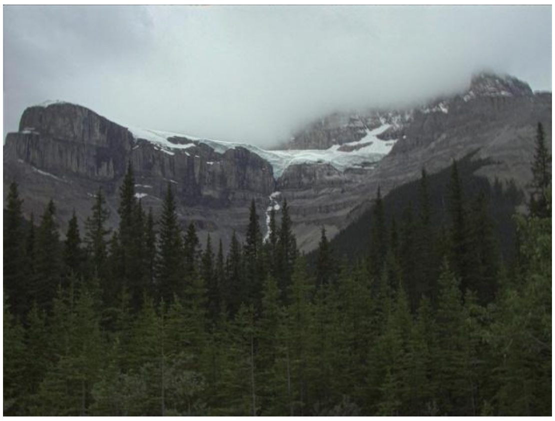


d) Desk.jpg **e) Reference** **f) SSIM=0.9939**





f) Memorial.jpg **g) Reference** **h) SSIM=0.9976**



l) crowfoot.jpg

m)Reference

n) SSIM=0.9978

Figure 8: Examples of smooth context-based color transfer for tone mapping

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