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Gradient-Preserving Color Transfer

Xuezhong Xiao[1] and Lizhuang Ma[1]

[1]Department of Computer Science & Engineering, Shanghai Jiao Tong University, China

Abstract

Color transfer is an image processing technique which can produce a new image combining one source image's contents with another image's color style. While being able to produce convincing results, however, Reinhard et al.'s pioneering work has two problems—mixing up of colors in different regions and the fidelity problem. Many local color transfer algorithms have been proposed to resolve the first problem, but the second problem was paid few attentions.

In this paper, a novel color transfer algorithm is presented to resolve the fidelity problem of color transfer in terms of scene details and colors. It's well known that human visual system is more sensitive to local intensity differences than to intensity itself. We thus consider that preserving the color gradient is necessary for scene fidelity. We formulate the color transfer problem as an optimization problem and solve it in two steps—histogram matching and a gradient-preserving optimization. Following the idea of the fidelity in terms of color and gradient, we also propose a metric for objectively evaluating the performance of example-based color transfer algorithms. The experimental results show the validity and high fidelity of our algorithm and that it can be used to deal with local color transfer.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Image Processing and Computer Vision]: Transform methods—

1. Introduction

Color transfer is an image processing technique which conveys the color characteristics of a reference image to a source image. Ideally, the result by a color transfer algorithm should keep the scene from the source image and apply the color style of the reference image. A good color transfer algorithm should provide fidelity both in terms of scene details and colors.

Reinhard et al. [RAGS01] originally presented a simple and efficient color transfer algorithm which translates and scales an image pixel-by-pixel in $l\alpha\beta$ color space according to the mean and standard deviation of the color values in the source and reference images. While this produces convincing results, this approach still has two problems. Firstly, it can produce unnatural looking results in cases where the source and reference images have different color distributions. Secondly, as the algorithm is based on simple statistics (mean and standard deviation), it can produce results with low fidelity in scene details and color distribution (Figure 1, 2). The first problem is widely known and many algorithms have been proposed to resolve it, e.g. swatch-based methods [RAGS01, WAM02], Chang et al.'s perceptual color category-based algorithm [CSN03,CSN07], EM-based soft color segmentation approach [TJT05, TJT07], Gaussian probability weighted color transfer method [WHCO08]. A main contribution of this paper is a solution to the second problem, which could be used with such techniques.

In this paper, we focus on fidelity of color transfer: the extent to which the produced result accurately reproduces the scene in the source image and the color distribution of the reference image. Pitie et al.'s method of n-dimensional probability density function (pdf) matching carries out the fidelity of color distribution, but it produces extra edges (Figure 1(d)). It is well known that the human visual system is more sensitive to local intensity differences than to intensity itself [LM71, Wer35]. We thus consider that preserving the color gradient is necessary to scene fidelity. We use a histogram to assess color. Combining gradients and a histogram gives a basis for a gradient-preserving color transfer algo-

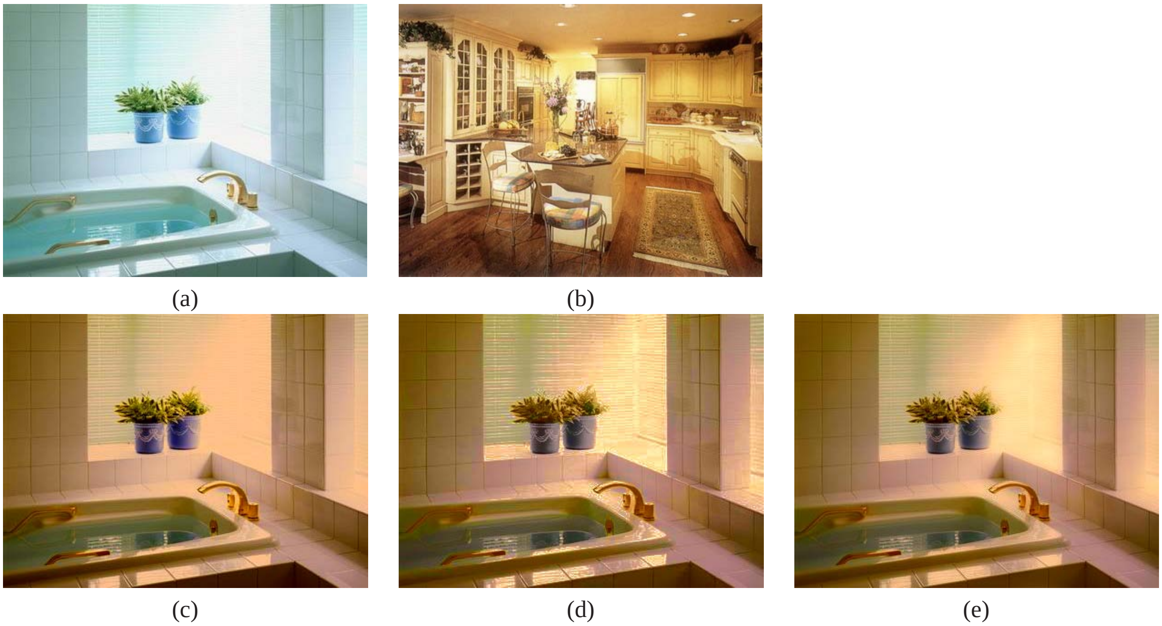


Figure 1: *Comparison among color transfer algorithms (Example #1): (a) a source image; (b) a reference image; (c) the result by Reinhard et al.'s algorithm; (d) the result by Pitie et al.'s method; (e) the result by our algorithm. Note that the color of the flowerpot in (c) is out of the color range of the reference image (b) and the extra details in (d) is not in the source image (a).*

rithm and an objective evaluation metric for example-based color transfer.

In summary, this paper makes the following contributions: (i) a gradient-preserving color transfer algorithm which can integrate more accurately the two key components of color transfer—we attempt to preserve the source image's color gradient and the reference image's color style, and (ii) a simple and effective metric to measure fidelity in terms of gradient and color.

2. Related Work

Recently, color transfer has become a fruitful research topic. We may classify these color transfer methods into global and local algorithms.

Reinhard et al.'s pioneering work [RAGS01] presented a global algorithm for transferring one image's color style to another. Just as what they found, the performance of color transfer is impacted by the source and reference images' similarity in composition. Reinhard et al. proposed a local method based on the inverse distance weighting to remedy it. After that, several local approaches were devised to make up the deficiency.

Chang et al. proposed a color category-based color transfer algorithm [CSN03] and extended it to process video data [CSN07]. Firstly, they converted the source and reference images to CIE $L^*a^*b^*$ color space and categorized each pixel as one of the eleven basic categories. Then, a convex hull was generated in color space for each category of pixel point set. Finally, color transformation was applied within each pair of convex hull of the same category.

Tai et al.'s local color transfer approach was based on their soft color segmentation algorithm [TJT05, TJT07]. Firstly, a modified EM algorithm was proposed to segment probabilistically the input images and construct GMMs (Gaussian Mixture Models) for them. Then, the corresponding relationships were obtained to map each Gaussian component in the source image to some Gaussian in the reference image. Finally, Reinhard et al.'s method was applied on each Gaussian component pairs and the intermediate results were combined fractionally according to each pixel's probability.

Wen et al. proposed a system for image enhancement by using a new color transfer algorithm [WHCO08]. The system provided users with a stroke-based user interface for specifying the unchanged background and the corresponding regions on the source and reference images. Firstly, an improved Graph-Cut algorithm was employed to segment the background. Then, a Gaussian probability weighted color transfer algorithm was presented to transform the source image according to the relevant strokes. But the direct algorithm can result in artifacts. So the authors used a gradient-based smoothness term to improve it.

Welsh et al. extended the idea of color transfer to colorize gray-scale images [WAM02]. Their algorithm computes the chromatic values of a pixel through a luminance matching guided by the statistics within the pixels' neighborhood. Rectangular swatches are used to achieve local matching.

In summary, aforementioned local methods basically rely on their classification schemes to successfully produce good results, e.g. Chang et al.'s eleven basic categories, Tai et al's soft color segmentation, wen et al.'s Gaussian probability weighting. We believe that these classification schemes can be combined with global color transfer algorithms to achieve local color transfer. Therefore, we mainly focus on global processing in this paper.

Pitie et al. [PKD05] presented a general *n*-dimensional pdf transfer method through the iteration of rotation of axis following several one-dimensional marginal matching and proved its convergence. The *n*-dimensional pdf transfer algorithm can be utilized to globally transfer colors between images. It obviously guarantees the preservation of color distribution. But unfortunately, it is easy to stretch excessively pixel values and results in the change of content (see Figure 1(d)). So, Pitie et al. proposed a softening scheme to remedy it.

Our algorithm is derived from the idea of fidelity in terms of gradient and color. In a sense, our method belongs to the domain of gradient manipulation which has recently become a very popular and hot research topic [AR07]. The techniques are widely used in many applications including HDR (High Dynamic Range) compression [FLW02, MMS06], local adjustment of tone [LFUS06], multi-scale decomposition of images [FFLS08], non-photorealistic rendering [MP08], etc.

Evaluation metrics are very important for evaluating algorithms' performance. PSNR (Peak Signal-to-Noise Ratio) and MSE (Mean Squared Error) are the most popular metrics because of their simplicity in understanding and implementation [WM08]. We proposed a metric for the objective evaluation of global color transfer algorithms following the idea of MSE. Compared with Xiang et al.'s [XZL09], our metric is more appropriate for example-based color transfer because the colorfulness similarity metric in Xiang et al.'s method is for the purpose of quality measurement instead of fidelity [HS03].

3. Gradient-Preserving Color Transfer

Our gradient-preserving color transfer algorithm is now explained. Color transfer has two goals: retaining the elements of the original scene in their correct color relationships, while applying the desired color style. To do so, our approach makes a compromise between retaining color gradient information from the source image, and applying the colors from the reference image. To achieve a perceptually plausible result, we take the preservation of a source image's gradient map and a reference image's histogram as our target. Thus, we formulate the color transfer problem as an optimization problem which minimizes the following cost function in terms of least-squared error:

$$\sum_k [H_k(o) - H_k(r)]^2 + \lambda \sum_p \|\nabla s_p - \nabla o_p\|^2 \qquad (1)$$

while o, r and s represent the output image, the reference image and the source image respectively; $H(\cdot)$ denotes a color histogram of the relevant image; ∇ is a gradient operator; λ is a coefficient for weighting the importance of gradient preservation and new colors, usually $\lambda = 1$. The first sum is taken over histogram bins, the second sum is taken over pixels in each image.

Equation 1 is hard to solve because the function $H(\cdot)$ is a statistical operation acting on the image as a whole while the gradient operator is applied to each pixel in an image. Therefore, we split the optimization into two steps and solve two consecutive tasks. In the first step, a histogram matching algorithm is employed to convert the source image s into an intermediate image f which now has exactly the same color style as the reference image g. Then, the optimization equation (Eq. 1) can be rewritten as

$$\sum_i (o_i - f_i)^2 + \lambda \sum_j \left[\left(\frac{\partial o_j}{\partial x} - \frac{\partial s_j}{\partial x} \right)^2 + \left(\frac{\partial o_j}{\partial y} - \frac{\partial s_j}{\partial y} \right)^2 \right] \qquad (2)$$

which means the output image o is expected to preserve the color of the intermediate image f and the gradient of the source image s. The two sums are taken over pixels in the relevant images.

Equation 2 is rewritten again by using matrix notation, and then the minimization problem can be defined as the solution of the following linear system:

$$\left[I + \lambda (D_x^T D_x + D_y^T D_y) \right] o = f + \lambda (D_x^T D_x + D_y^T D_y) s \qquad (3)$$

while D_x and D_y denote the matrix form of gradient operator along the x and y axis, respectively. In our implementation, D_x and D_y are forward Sobel difference operators; D_x^T and D_y^T are backward Sobel difference operators.

Equation 3 is a huge scale linear system of equations. Although the coefficient matrix is sparse, solving such linear system could consume a great deal of memory and CPU time. Researchers have presented many solutions to the problem. Among them, a quadtree-based technique [Aga07] and a multigrid method [BFGS03] fit our uses because the former can decrease the scale of the problem and the latter increases the efficiency of computation.

4. Evaluation Metric

There are few objective metrics proposed for evaluating the performance of color transfer algorithms. Xiang et al. [XZL09] combined Hasler and S*ü*sstrunk's colorfulness similarity metric [HS03] with Chen et al.'s gradient-based structural similarity metric [CYX06] to measure the performance of color transfer algorithms. Howbeit, Hasler and

Süsstrunk have proclaimed in their paper that their method measures quality but not fidelity [HS03]. That is, the colorfulness metric is designed to evaluate the overall colorfulness of an image rather than to measure the difference between two images. So Xiang et al.'s metric is not suitable to our application (i.e. example-based color transfer).

We consider that the scene details in the source image and the color style of the reference image are the two key components in the processing of example-based color transfer. Therefore, we propose a metric in terms of gradient and histogram to measure the performance of example-based color transfer algorithms. Following the idea of MSE, we define the metric as follows,

$$\begin{aligned} MSE &= MSE_{hist} + \lambda \cdot MSE_{grad} \\ &= \frac{1}{M}\sum_{k=1}^{M}[H_k(o) - H_k(r)]^2 \\ &+ \lambda \cdot \frac{1}{N}\sum_{j=1}^{N}\left[G(o_j) - G(s_j)\right]^2 \end{aligned} \tag{4}$$

while M is the number of the bins of a histogram; N is the total number of pixels in an image; λ is a weighting coefficient and we set $\lambda = 1$ to represent the equivalent importance between color and gradient; $H(\cdot)$ and $G(\cdot)$ denote the color histogram and gradient map of the relevant image, respectively. Here, we compute the gradient maps of color images by using Di Zenzo's algorithm [Zen86]. The values of MSE vary inversely with fidelity.

5. Experimental Results

In this section, we show the results produced by our algorithm and compare our method with previous algorithms. The experimental environment involves a computer with a 3GHz CPU of Intel Core 2 Duo and 4GB memory, 32-bit Windows operating system, and Matlab version 7.7. The experiments show that our algorithm has lower computation efficiency. But our method focuses on the fidelity in terms of gradient map and color distribution.

Our gradient-preserving color transfer algorithm is an example-based global method. So we compared it with Reinhard et al's algorithm [RAGS01] and Pitie et al.'s histogram matching method [PKD05]. Figure 1 and 2 show several examples (Example #1 – #4) of the comparison among the three color transfer algorithms. From the figures, we can find that Reinhard et al.'s algorithm might produce colors which are out of the color range of the reference images (see the flowerpot in Figure 1(c) and the red leaves of Example #4 in Figure 2(d)). While Pitie et al.'s approach have the effects of image enhancement, it produces more extra details from the view of fidelity and sometimes its result looks like noised (Example #3 in Figure 2(c)). Furthermore, we can find that the results of Reinhard et al's and Pitie et al.'s algorithms lose the details of the house in Example #3, but our approach keep the house clear through the method of gradient-preserving.

We also use our metric (Eq. 4) to measure the errors of the results by the three algorithms. The line charts in Figure 3 illustrate the comparison of performance in MSE. MSE assess synthetically the fidelity of algorithms in terms of gradient and color distribution, and our algorithm has the best and stable performance in the objective evaluation metric MSE.

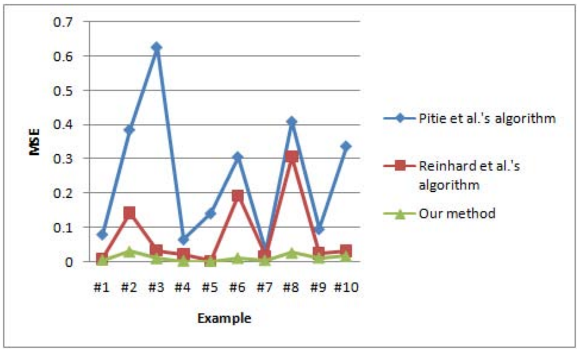


Figure 3: *Evaluation metric in terms of color and gradient.*

Figure 4 exhibits the different results corresponding to different coefficients λ in Equation 3. Obviously, the result is failed while $\lambda = 10$. We find that the value of MSE in Equation 4 varies following the variation of λ and the minimal values are usually located near 1 for the examples in this paper. Thus, we normally set $\lambda = 1$ for our experiments.

Utilizing previous local methods mentioned in Section 2 to compute the corresponding regions in the source and reference images, our approach can deal with local conditions. Also, the corresponding relationship can be specified by users. Figure 5 shows two examples of our algorithm in local color transfer. Users edited the masks to construct the corresponding relationship of blocks in the source and reference images (the reference images and their masks are not showcased in Figure 5). These examples exhibit that our algorithm can produce natural results even if the masks are rough.

Figure 6 shows more examples of our gradient-preserving color transfer algorithm (Example #5 – #10).

We implement Reinhard et al.'s, Pitie et al.'s, and our algorithms in Matlab 7.7. Table 1 shows the execution time of the Matlab codes of the three algorithms for the ten examples showed in Figure 1, 2 and 6. We can find that the computational speed is the disadvantage of our method. The main consumer of CPU time in our algorithm is in the step of solving a huge-scale linear system of equations. There exist many efficiet techniques of solving huge-scale linear equations which were reported owning realtime performance, e.g. Agarwala's quadtree-based scale reduction method [Aga07],

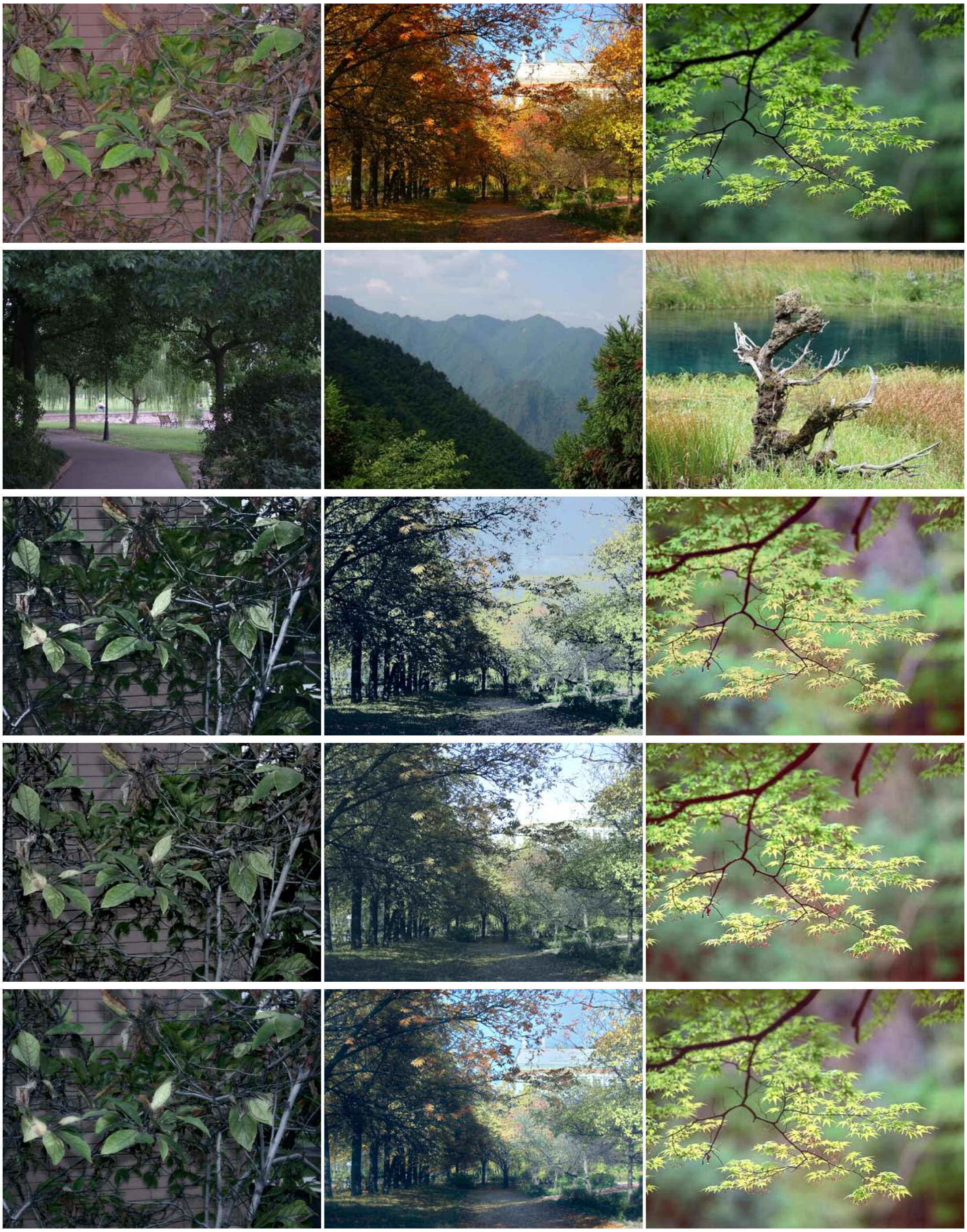
(a)

(b)

(c)

(d)

(e)

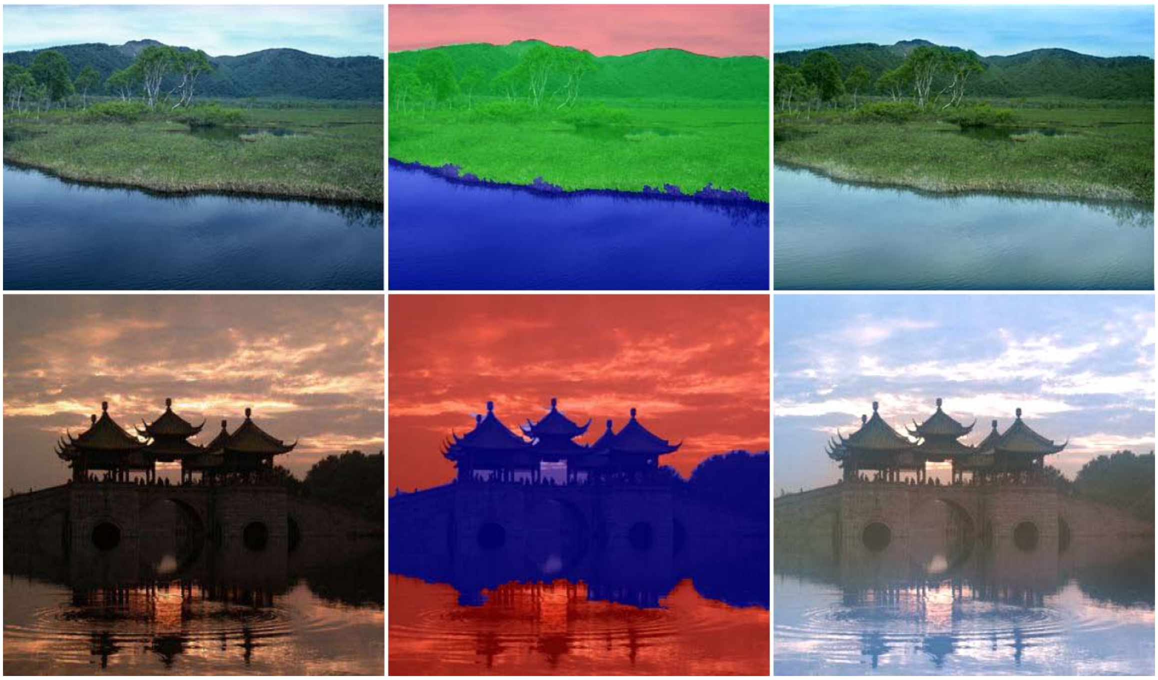


Example #2 Example #3 Example #4

Figure 2: *Examples of the comparison among color transfer algorithms: (a) source images; (b) target images; (c) the results by Pitie et al.'s algorithm; (d) the results by Reinhard et al.'s algorithm; (e) the results by our method.*

(a) Source image (b) Reference image (c) $\lambda = 1$ (d) $\lambda = 10$

Figure 4: *The example showcases the variation of our results while the weighting coefficient λ is changed.*



(a) Source images (b) Color-masked source images (c) Our results

Figure 5: *Examples of our algorithm in local conditions. The masks are utilized to construct corresponding relationships between the blocks in the source and reference images.*

Bolz et al.'s generalized GPU multigrid method [BFGS03]. Therefore, we have reasons to believe that our gradient-preserving color transfer algorithm can be improved significantly in speed after using these acceleration methods.

6. Conclusion and Future Work

In this paper, we present a novel gradient-preserving color transfer algorithm. To achieve a perceptually plausible result, it is necessary for color transfer with high fidelity to preserve the gradients of source images and the color distribution of reference images. Then, we formalize the targets as solving an optimization problem with two steps and solve them successfully. Also, we propose an evaluation metric for measuring the fidelity of global color transfer algorithms objectively. The experimental results verify our algorithm's effectiveness and high fidelity and that it can be used to deal with local color transfer.

Although our technique can acquire high fidelity in terms of gradient and color, it needs more computing resources including time and memory for it involves solving a huge-scale linear system of equations. Despite it can be real-time after utilizing acceleration algorithm, e.g. the generalized GPU multigrid methods [BFGS03,GWL*03] and Agarwala's quadtree-based technique [Aga07], our algorithm is less efficient in time and space than Reinhard et al.'s method. Therefore, users should weigh the efficiency and fidelity to choose Reinhard et al.'s algorithm or ours.

In the future, we plan to research on more effi-

#5

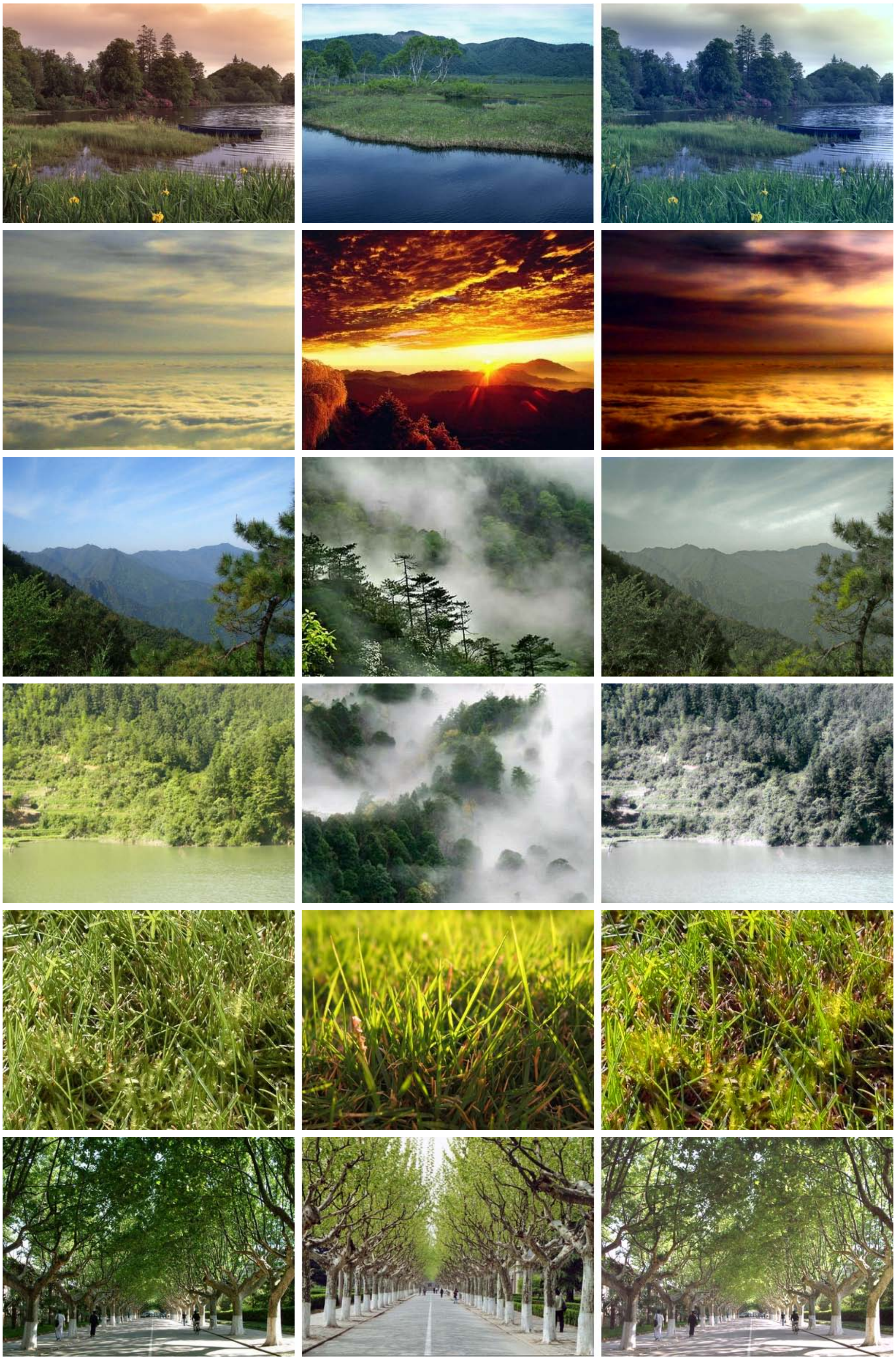
#6

#7

#8

#9

#10



(a) Source images (b) Reference images (c) Our results

Figure 6: *Some examples of our gradient-preserving color transfer.*

Example	Execution Time (seconds)		
	Pitie et al.	Reinhard et al.	Ours
#1	0.61	0.092	2.14
#2	0.49	0.096	2.15
#3	0.51	0.096	2.18
#4	0.57	0.091	2.10
#5	0.51	0.095	2.19
#6	0.56	0.103	2.26
#7	0.55	0.096	2.11
#8	0.56	0.097	2.06
#9	0.56	0.097	2.17
#10	0.56	0.097	2.13

Table 1: *Execution time of the Matlab codes (our implementation) of Pitie et al.'s, Reinhard et al.'s, and our algorithms.*

cient methods of solving huge-scale linear equations, and gradient-domain manipulation techniques for image and video processing, e.g. the vectorization of images and videos [ZCZ*09, LHM09].

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