

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/234755199>

Fast local color transfer via dominant colors mapping

Article · January 2010

DOI: 10.1145/1899950.1899996

CITATIONS

21

READS

851

4 authors, including:



Weiming Dong

Chinese Academy of Sciences

86 PUBLICATIONS 859 CITATIONS

[SEE PROFILE](#)



Guanbo Bao

Chinese Academy of Sciences

15 PUBLICATIONS 153 CITATIONS

[SEE PROFILE](#)



Xiaopeng Zhang

Chinese Academy of Sciences

210 PUBLICATIONS 2,003 CITATIONS

[SEE PROFILE](#)

Some of the authors of this publication are also working on these related projects:



Project Data-Driven Image Synthesis [View project](#)



Project E-skeleton / Squelette Ellipsoidal [View project](#)

Fast Local Color Transfer via Dominant Colors Mapping

Weiming Dong^{1,2}

Guanbo Bao¹

Xiaopeng Zhang¹

Jean-Claude Paul²

¹LIAMA-NLPR-Digital Content Technology Research Center, CAS Institute of Automation, China

²INRIA, France



(a) Source image

(b) Target image

(c) Ours

(d) Tai et al. [2005]

Figure 1: A comparison of our method and the result via probabilistic segmentations [Tai et al. 2005]. Our result looks more natural. Note that some areas in (d) fail to be depicted by the color styles in (b), such as the blue in the sky and the red in the grassland. Our method separately uses the dominant color styles in (b) to depict the corresponding areas in (a) and also preserves the details of the original scene.

1 Introduction

Color transfer is an image editing technique which arises various applications, from daily photo appearance enhancement to movie post-processing. An ideal color transfer algorithm should keep the scene from the source image and apply the color style of the target image. All the dominant colors in the target image should be transferred to the source, while the colors in the source image which are apparently distinct from the target style should not appear in the result. The preservation of the scene details is also important for a good color transfer algorithm.

Reinhard et al. [2001] first presented global color transfer algorithm according to the mean and standard deviation of the color values in the source and target image, after translating the RGB space to the uncorrelated color space $l\alpha\beta$. The method is efficient but in most cases artifacts are caused when the source and target images have different color distributions. Region-by-region transfer is performed using automatic image segmentation algorithms [Tai et al. 2005; Pitié et al. 2007]. This kind of local color transfer techniques are easy to implement, automatic and work for a large variety of scenarios, even when the target image is very different from the processed images. However, these approaches still have two problems. Firstly, they can produce unnatural looking results in cases when the regions of the source and target images are not accurately matched, some pixels in the result image may fail to be transferred to the color style of the target (Figure 1(d)). This problem is usually caused by the excessively soft segmentation for the images. Secondly, some local details of the source image could be smoothed or even erased during the transfer process, especially when some regions with similar colors are mapped to the same local distribution of the target. This produces results with low fidelity in scene details and local color contrast.

We present a novel algorithm to address the above issues. Our method establishes a tight connection between the local color statistics of the source and target images. All the obvious color features can be presented in the result image. We also balance the color style and the source gradient to preserve the fidelity of the scene.

2 Algorithm Details

In our algorithm, the transfer is done in color space $l\alpha\beta$ which has uncorrelated components and accounts for human-perception

of colors. In order to establish the connections between the color features of the source and target images, we first extract the DCD (Dominant Color Descriptor) of the images:

$$F = \{p_j, \mathbf{c}_i, v_i\}, \quad i = 1, 2, \dots, N. \quad (1)$$

where N is the number of dominant colors ($N = 32$ in our experiments), p_i is the percentage of pixels in the image corresponding to the i th dominant color, \mathbf{c}_i is a vector representing the i th dominant color, and v_i is the variation of the dominant color values of the pixels around \mathbf{c}_i . In our system, we always extract the same number of dominant colors from both the source and the target images. Ideally, the final result should construct from the scene of the source image and use the target color style which is represented by the dominant colors. And visually the regions with different colors (including the colors of the same chrominance) in the source image should also appear with different color features in the result. To achieve this objective, we find a one-to-one mapping between the dominant color set of the two images, the metric defined as

$$d(\mathbf{c}^s, \mathbf{c}^t) = \min_{\phi} \sum_{i=1}^N d_e(\mathbf{c}_{\phi(i)}^s, \mathbf{c}_i^t), \quad (2)$$

where ϕ belongs to the set of permutations of $\{1, \dots, N\}$. We adopt EMD (Earth Mover's Distance) [Rubner et al. 2000] to optimize the cost of the mapping in Equation (3). In our implementation, each color feature is given the same weight, then the computation of the EMD is reduced to an assignment problem. This means that each dominant color of the source image is assigned to exactly one dominant color of the target one. We use an exponential distance to compute the distance between two features:

$$d_e(\mathbf{c}_{\phi(i)}^s, \mathbf{c}_i^t) = 1 - e^{-\left(\frac{\sqrt{(l_{\phi(i)}^s - l_i^t)^2 + (\alpha_{\phi(i)}^s - \alpha_i^t)^2 + (\beta_{\phi(i)}^s - \beta_i^t)^2}}{\delta} \right)}, \quad (3)$$

where we set $\delta = 15$ in our algorithm. Since the number of dominant colors is small in our algorithm, we can achieve real-time performance for the EMD optimization process.

In our algorithm, we also use soft boundaries for the source image to partly solve the artifacts caused by the segmentation, like Tai et al. [2005]. Instead of computing the probabilities to all the dominant colors for each pixel, we only check the ones in its neighbor.



Figure 2: A comparison of our method and the technique using pdf mapping [Pitié et al. 2007]. Results show that our algorithm is more accurate in mapping the colors and better preserves both the scene contents and the details.

Denote $\mathcal{N}(x, y)$ as the neighbor of (x, y) , the probability that a pixel color $I(x, y)$ belongs to the i th DCD region is calculated as:

$${}_i P_{xy} = \frac{1}{Z_i} \sum_{(x', y') \in \mathcal{N}(x, y)} d(I(x, y), I'(x', y'))_i \quad (4)$$

where $Z_i = \sum_i \sum_{(x', y') \in \mathcal{N}(x, y)} d(I(x, y), I'(x', y'))_i$ is the normalization factor. We also use an adapted bilateral filter to simultaneously smooth the color and spatial information:

$$\begin{aligned} d(I(x, y), I'(x', y')) &= \alpha \cdot e^{-\left(\frac{\sqrt{(x-x')^2+(y-y')^2}}{\delta_s}\right)} \\ &+ (1-\alpha) \cdot e^{-\left(\frac{|I(x, y)-I(x', y')|}{\delta_c}\right)}. \end{aligned} \quad (5)$$

The parameter α balances color and spatial contributions. Parameters δ_s and δ_c are chosen according to the color and spatial dynamics. Typical values used in our experiments are $\alpha = 0.4$, $\delta_c = 0.05$ and $\delta_s = 4$. This item guarantees the smoothness alongside the region boundaries.

Similar as [Tai et al. 2005], we calculate the mean μ_i and standard deviation σ_i of each region in the source image as:

$$\mu_i^s = \frac{1}{Z} \sum_{x, y} {}_i P_{xy} I(x, y) \quad (6)$$

$$\sigma_i^s = \sqrt{\frac{\sum_{x, y} {}_i P_{xy} (I(x, y) - \mu_i)^2}{Z}} \quad (7)$$

where Z is the normalization factor, which is equal to $\sum_{x, y} {}_i P_{xy}$. Different with [Tai et al. 2005], our algorithm does not require the EM optimization for the GMM estimation, and only the source image needs the above spatial smoothing process, so the speed is very fast. Then, we compute the output transferred color pixel $I^o(x, y)$ as

$$I^o(x, y) = \sum_i \phi(i) {}_i P_{xy} \left(\frac{\sigma_i^s}{\sigma_{\phi(i)}^t} I^s(x, y) - \mu_{\phi(i)}^t \right) + \mu_i^s, \quad (8)$$

where $\phi(i) {}_i P_{xy}$ is the probability that the source pixel $I^s(x, y)$ is mapped to dominant color $\phi(i)$ of the target image. Finally, we employ the gradient-preserving color transfer method in [Xiao and Ma 2009] to recover the details of the original scene.

3 Results and Conclusion

In Figure 1, we compare our method with the local color transfer method in [Tai et al. 2005]. Our EMD-based color mapping assures

that all the dominant color styles are transferred to the source image. Our result looks more natural and no unexpected colors like the red color in Figure 1(d) appear in the image. In Figure 2, we can see that our result can accurately depict all the colors of the target image while Pitié et al.’s [2007] method can not. Some details of the original scene are also better preserved in our result.

In this paper, we present a novel local color transfer algorithm by mapping the dominant colors of the source image to the target. Our method is fast, fully automatic and can accurately depict all the dominant color styles of the target in the output image. The details of the original scene are also nicely preserved. In the future, we plan to research on more efficient methods of solving color mapping. The color transfer to videos is also a potential direction.

Acknowledgement

We thank Dr. Ning Zhou at Sony Corporation for the inspiring discussion of this work. The source, target and result images in Figure 1 are borrowed from [Tai et al. 2005], and those in Figure 2 are borrowed from [Pitié et al. 2007]. This work is supported in part by National Natural Science Foundation of China No. 60970093, 61072151, 60872120, and 60902078, in part by SRF for ROCS, SEM, in part by ANR-NSFC No. 60911130368, and in part by the Strategic Cooperation between Project Guangdong Province and Chinese Academy of Sciences No. 2009B091300044.

References

- PITIÉ, F., KOKARAM, A. C., AND DAHYOT, R. 2007. Automated colour grading using colour distribution transfer. *Comput. Vis. Image Underst.* 107, 1-2, 123–137.
- REINHARD, E., ASHIKHMİN, M., GOOCH, B., AND SHIRLEY, P. 2001. Color transfer between images. *IEEE Comput. Graph. Appl.* 21, 5, 34–41.
- RUBNER, Y., TOMASI, C., AND GUIBAS, L. J. 2000. The earth mover’s distance as a metric for image retrieval. *Int. J. Comput. Vision* 40, 2, 99–121.
- TAI, Y.-W., JIA, J., AND TANG, C.-K. 2005. Local color transfer via probabilistic segmentation by expectation-maximization. In *Proceedings of CVPR’05 - Volume 1*, IEEE Computer Society, Washington, DC, USA, 747–754.
- XIAO, X., AND MA, L. 2009. Gradient-preserving color transfer. *Computer Graphics Forum* 28, 7, 34–41.