

See discussions, stats, and author profiles for this publication at: <http://www.researchgate.net/publication/254002890>

Distribution-aware image color transfer

ARTICLE · JANUARY 2011

DOI: 10.1145/2077378.2077388

CITATIONS

2

READS

73

6 AUTHORS, INCLUDING:



[Fuzhang Wu](#)

Chinese Academy of Sciences

7 PUBLICATIONS 4 CITATIONS

SEE PROFILE



[Weiming Dong](#)

Chinese Academy of Sciences

50 PUBLICATIONS 179 CITATIONS

SEE PROFILE



[Xing Mei](#)

Chinese Academy of Sciences

30 PUBLICATIONS 162 CITATIONS

SEE PROFILE



[Xiaopeng Zhang](#)

Chinese Academy of Sciences

127 PUBLICATIONS 508 CITATIONS

SEE PROFILE

Distribution-Aware Image Color Transfer

Fuzhang Wu¹ Weiming Dong^{1,3} Xing Mei¹ Xiaopeng Zhang¹ Xiaohong Jia² Jean-Claude Paul³
¹LIAMA-NLPR, CAS Institute of Automation, China ²KLMM, AMSS, CAS, China ³INRIA, France



Figure 1: Comparison of our algorithm with the local color transfer method [Dong et al. 2010]. For the source image, we use a mask to indicate that only the yellow flowers are processed. Note that in our result (c), not only all the dominant color styles but also their spatial distribution in (b) is presented.

1 Introduction

Color transfer is a practical image editing technology which is useful in various applications. An ideal color transfer algorithm should keep the scene in the source image and apply the color styles of the reference image. All the dominant color styles of the reference image should be presented in the result especially when there are similar contents in the source and reference images.

Reinhard et al. [2001] present a global color transfer algorithm which manipulates the pixel value of source image to match the global mean and standard deviation of the reference image in a uncorrelated color space $l\alpha\beta$. Unnatural results may be produced when the color distributions of source and reference images are very different. Dong et al. [2010] extract the same number of dominant color descriptor (DCD) from the input images and find an optimal one-to-one mapping between the dominant color sets. All the obvious color styles of the reference image can be presented in the result if there are enough corresponding dominant color patterns in the source. However, as shown in Figure 1, the normal local color transfer algorithms will fail to generate a satisfied result if the number of source dominant colors is much less than the reference one, especially when the color styles are transferred between similar contents. Moreover, the spatial distribution of the reference color pattern should also be considered during the transfer process.

We propose a robust color transfer framework to address the above issues. Our method can establish a soft connections between the local color statistics of the source and reference images. All the obvious color features can be presented in the result image, as well as the spatial distribution of the reference color pattern.

2 Algorithm Details

We first use Mean Shift method [Comaniciu and Meer 2002] to segment the images into different regions. Each region contains pixels with a similar color style. We call the regions as Dominant Color Regions (DCR), which can be denoted as:

$$R_i = \{p_i, \mathbf{x}_i, \boldsymbol{\mu}_i, \boldsymbol{\sigma}_i, \mathbb{S}_i\}, \quad i = 1, 2, \dots, N. \quad (1)$$

where N is the number of DCR, p_i is the percentage of pixels in the image corresponding to the i th DCR, \mathbf{x}_i is a vector representing the geometric center, $\boldsymbol{\mu}_i$ and $\boldsymbol{\sigma}_i$ are the color mean and standard

deviation value of the region, \mathbb{S}_i is the pixel set of the i th DCR. The geometric center \mathbf{x} is normalized to the range $[0, 1]$.

We adopt EMD (Earth Mover's Distance) [Rubner et al. 2000] method to find an optimal mapping between the DCR sets of the source and reference images. Unlike the tight mapping method [Dong et al. 2010], we construct a soft many-to-many mapping between the two DCR sets. Denote f_{ij} as the probability of the i th source DCR maps to the j th reference DCR, and d_{ij} as the distance between them, the cost of the mapping is optimized by:

$$\min_{\{f_{ij}\}} \sum_{i=1}^{N_s} \sum_{j=1}^{N_r} f_{ij} d_{ij} \quad (2)$$

$$\text{subject to } \sum_{j=1}^{N_r} f_{ij} = p_i^s, \quad \sum_{i=1}^{N_s} f_{ij} = p_j^r,$$

where N_s, N_r denote the number of DCRs, p_i^s and p_j^r denote the percentage of pixels in the image corresponding to the DCR (s, r denote the source and reference image respectively). Each DCR is given the same weight, which means the DCRs have equal importance. By optimizing Equation (2), the source DCRs are softly mapped to the corresponding reference ones. In order to transfer the spatial distribution of the reference color styles, we add the geometric location information to construct the distance function. We use an exponential distance to calculate the distance between two DCRs:

$$d_{ij} = \exp\left(\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{\delta_s}\right) \cdot \exp\left(\frac{\|\boldsymbol{\mu}_i - \boldsymbol{\mu}_j\|^2}{\delta_c}\right), \quad (3)$$

where $\|\cdot\|$ denotes the l_2 norm, δ_s and δ_c are parameters to control the contributions of geometric location and color information respectively ($\delta_s = 0.6$ and $\delta_c = 1.0$ in our experiments).

After solving Equation (2), we can formulate a transform function to map each source DCR to the reference ones:

$$\Phi(R_i^s) = \frac{\sum_{j=1}^{N_r} f_{ij} R_j^r}{\sum_{j=1}^{N_r} f_{ij}}, \quad (4)$$

where R_i^s, R_j^r denote $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ of the i th source and the j th reference region respectively. This function maps each source DCR to corresponding reference DCRs by a weighted average of them.

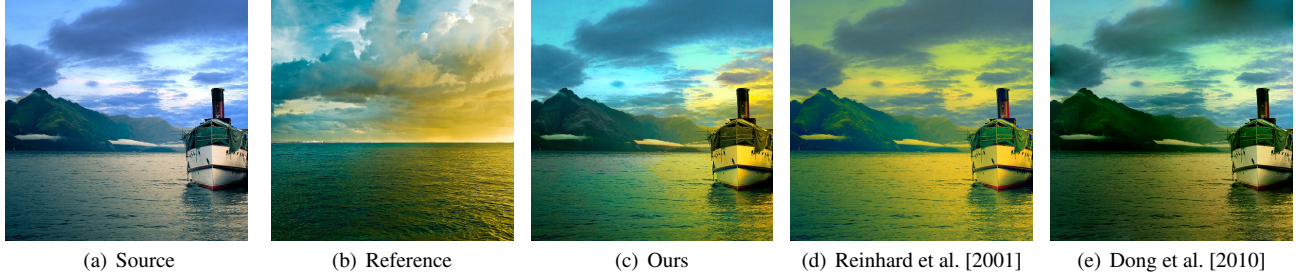


Figure 2: Comparison of our algorithm with other methods. Our result is more visually natural and semantically rational than the others. Note that the blue style in the reference sky is not presented in (d), and the yellow style in the reference sky is not transferred to the sky area in (e). Our result (c) simultaneously depicts all the dominant color styles and preserves the spatial distribution of the reference color.

We use a soft boundary for the source image to avoid the artifacts causing by segmentation. When transferring the pixel color $I(x, y)$, we consider the contribution of the neighbour dominant color regions. Assume R_i is the region to which pixel $I(x, y)$ belongs, we define the neighbour DCRs of pixel $I(x, y)$ as:

$$N(x, y) = \{R_i\} \cup \{R_j | \exists I(x_i, y_i) \in \mathbb{S}_i, I(x_j, y_j) \in \mathbb{S}_j : |x_i - x_j| + |y_i - y_j| = 1\}, \quad (5)$$

For each neighbour region $R_j \in N(x, y)$, we calculate the probability that the pixel color $I(x, y)$ belongs to it as:

$${}_jP_{xy} = \frac{1}{Z} D(I(x, y), R_j), \quad (6)$$

where $Z = \sum_{R_j \in N(x, y)} D(I(x, y), R_j)$ is the normalization factor, and $D(I(x, y), R_j)$ is the similarity between the pixel color $I(x, y)$ and the neighbour region R_j . We adopt bilateral filter to smooth the color and spatial similarity simultaneously:

$$D(I(x, y), R_j) = \exp\left(-\frac{(x - x_j)^2 + (y - y_j)^2}{\delta_s}\right) \cdot \exp\left(-\frac{\|I(x, y) - \mu_j\|^2}{\delta_c}\right), \quad (7)$$

where $\mathbf{x}_j = (x_j, y_j)$ is the geometric center of the j th source DCR. In our experiments we set $\delta_s = 0.4$ and $\delta_c = 1.0$.

Similar as the method in [Dong et al. 2010], we use the probability ${}_jP_{xy}$ to average the contributions of the neighbour regions $N(x, y)$ for the output pixel color $I^o(x, y)$. We get each pixel color $I^o(x, y)$ of the output image as:

$$I^o(x, y) = \sum_j {}_jP_{xy} \frac{\Phi(\sigma_j^s)}{\sigma_j^s} (I(x, y) - \mu_j^s) + \Phi(\mu_j^s), \quad (8)$$

where ${}_jP_{xy}$ is the probability that the pixel $I(x, y)$ belongs to the neighbour region R_j , $\Phi(\mu_j^s)$ and $\Phi(\sigma_j^s)$ are the new mapping mean and standard deviation of region R_j respectively. In our experiments, we use LAB color space in the transfer process. In order to preserve the original luminance and some details, the L channel can be kept in some cases.

3 Results and Conclusion

In Figure 1, we compare our algorithm with the DCD mapping-based method [Dong et al. 2010]. Our result depicts both the dominant color styles and their corresponding spatial distribution in the

reference image. The integration of the spatial distribution information guarantees all the dominant color styles are transferred to the source image, even if the number of the source dominant colors is less than the reference one. In Figure 2, we can note that the reference blue style is lost in Figure 2(d), and the yellow style in the reference sky is not transferred to the corresponding sky area in Figure 2(e), while in our result all the dominant color patterns are preserved in their original spatial distribution.

In this paper, we propose a novel local color transfer algorithm that integrates spatial distribution of reference dominant colors in the transfer process. Our method outperforms previous global and soft segmentation based local color transfer algorithms especially when the number of the source dominant color styles is much less than the reference one. The spatial distribution of the reference dominant color styles are also nicely preserved in the output image. In the future, we will explore a more intelligent method which can use object-level information in the transfer process.

Acknowledgement

We thank the following Flickr members for sharing their images on the internet: susanonline (yellow flowers), larrygerbrandt (wild flowers), ►CubaGallery (sea boat and sea sky), Thai Jasmine (purple flowers), Natasha Maiolo (seashore). Thank Hao Wang (boats) and Zhilei Zhang (sea sundown) for letting us use their photos. This work is supported by National Natural Science Foundation of China(No.60872120, 60902078, 61172104), by Beijing Natural Science Foundation(Content-Aware Image Synthesis and Its Applications, No.4112061), by French System@tic Paris-Region(CSDL Project) and ANR-NSFC(No.60911130368).

References

- COMANICIU, D., AND MEER, P. 2002. Mean shift: A robust approach toward feature space analysis. *IEEE Trans. Pattern Anal. Mach. Intell.* 24 (May), 603–619.
- DONG, W., BAO, G., ZHANG, X., AND PAUL, J.-C. 2010. Fast local color transfer via dominant colors mapping. In *ACM SIGGRAPH ASIA 2010 Sketches*, ACM, New York, NY, USA, SA '10, 46:1–46:2.
- REINHARD, E., ASHIKHMIN, M., GOOCH, B., AND SHIRLEY, P. 2001. Color transfer between images. *IEEE Comput. Graph. Appl.* 21 (September), 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.