Decomposition of shading and reflectance from a texture image

Hui-Liang Shen* and Ke Li

Department of Information and Electronic Engineering, Zhejiang University, Hangzhou 310027, China
**Corresponding author: shenhl@zju.edu.cn*

Received October 7, 2008; accepted November 13, 2008;
posted November 24, 2008 (Doc. ID 102456); published December 24, 2008

A method for decomposing shading and reflectance components from a color texture image is presented. The shading intensity of each pixel is either computed or synthesized according to its characteristics, and the reflectance is consequently decomposed, with additional denoising when necessary. The performance of the proposed method is evaluated using real color texture images. © 2008 Optical Society of America

OCIS codes: 100.3020, 100.2960, 330.1690.

For an object without specular reflection, the image intensity is determined by the interaction between two intrinsic components: shading and reflectance. The shading is affected by the lighting direction and surface geometry, and the reflectance describes the characteristic of light reflection. The appropriate decomposition of these two components is an important issue in computer vision and will benefit image content interpretation and scene simulation. In the literature, some works have been conducted to recover the shading of generic objects from one or more images [1,2].

Unlike previous works, this Letter attempts to accurately decompose the shading and reflectance components of color texture images with approximate regular texture structures, such as those of textile fabrics as shown in Fig. 1. The numbers of dominant colors are usually limited, but their spatial color distribution is complicated due to the yarn structures and imaging noise, which always makes the component decomposition difficult.

For a texture surface with only diffuse reflection, the intensity $I_c(p)$ of the cth channel $(c=1,2,3)$ at pixel position p is the product of a geometry term $g(p)$ and a reflectance term $\rho_c(p)$,

$$I_c(p) = g(p) \cdot \rho_c(p). \tag{1}$$

Without loss of generality, it is assumed that the reflectance intensities are constant for the pixels in the same region, and the color variations are due to surface geometry. Suppose there are K regions, let $\mathbf{m}(k)=[m_1(k),m_2(k),m_3(k)]^T$ be the representative color of the kth region. Suppose pixel p belongs to the kth region, Eq. (1) can be written as

$$I_c(p) = \alpha(p,k) m_c(k), \tag{2}$$

where $\alpha(p,k)$ is the shading intensity of pixel p with respect to the kth region. In a color image the $\alpha(p,k)$ is solved as

$$\alpha(p,k) = \mathbf{m}^{-}(k)\mathbf{I}(p), \tag{3}$$

where the superscript – denotes pseudo-inverse and $\mathbf{I}(p)=[I_1(p),I_2(p),I_3(p)]^T$. The pseudo-inverse of $\mathbf{m}(k)$ is calculated by using singular value decomposition [3].

Owing to the complicated spatial and color distribution, it is always difficult to classify every pixel into a region definitely [4]. In this Letter, we propose an
alternative strategy. For pixel p, its relative fitting error with respect to each region is computed as

$$e(p,k) = \frac{\|\mathbf{I}(p) - \alpha(p,k)\mathbf{m}(k)\|}{\|\mathbf{I}(p)\|} = \frac{\|\mathbf{I}(p) - \mathbf{m}(k)\mathbf{m}^{-}(k)\mathbf{I}(k)\|}{\|\mathbf{I}(p)\|}, \tag{4}$$

where $k=1\ldots K$. A pixel is classified to a certain region provided that its error is significantly smaller than those of other regions. More precisely, the label of pixel p should be

$$l(p) = \begin{cases} k & \text{if } e(p,k) \leqslant \eta e(p,j),\ j=1\ldots K, j \neq k \\ \text{ambiguous} & \text{otherwise} \end{cases}, \tag{5}$$

where η controls the stringent level and is set to be 0.5 in this Letter. Consequently, the initial shading intensity $\alpha(p)$ of unambiguous pixel p is $\alpha(p,l(p))$. For the boundary pixels in between adjacent regions, their colors are always the blend of two or more dominant colors. Accordingly, the initial shadings of these pixels are considered to be unreliable.

Generally, the texture strength of a region is related to the dominant color and is different from each other [see Fig. 1(b)]. To obtain a uniform shading dis-

 © 2009 Optical Society of America

(a) (b)

Fig. 1. (Color online) (a) Color texture image and (b) enlarged area.

tribution, the shading intensities of the unambiguous and nonboundary pixels are adjusted as

$$\tilde{\alpha}(p) = \frac{\alpha(p) - \mu_s}{\sigma_s}\sigma_t + \mu_t, \qquad (6)$$

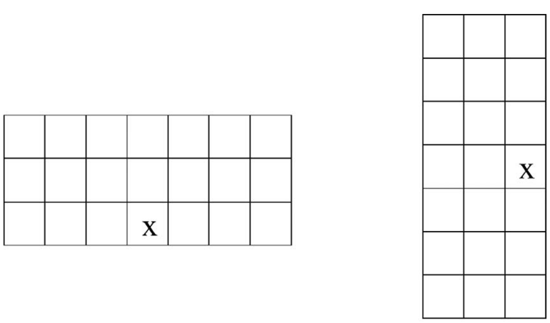
where μ_s and σ_s are the mean and standard deviation of the shading of the region that pixel p belongs to and μ_t and σ_t are the mean and standard deviation of the shadings of the reference region.

To generate shadings for the ambiguous and boundary pixels, we present a technique referred as "shading synthesis," which is inspired by the texture synthesis technique [5]. Figure 2 shows two neighborhoods for shading synthesis. The 7×3 horizontal neighborhood is for the approximately vertical boundaries, whereas the 3×7 vertical neighborhood is for approximately horizontal boundaries. The shading synthesis runs on the image in scan-line order. The best matched pixel q is the one whose neighboring shading distribution most closely resembles that of the pixel p currently under processing as described in the following:

$$\alpha(p) = \arg\min_{\alpha(q)}\left[\sum_{p^*,q^*}(\alpha(p^*) - \alpha(q^*))^2\right]^{1/2}, \qquad (7)$$

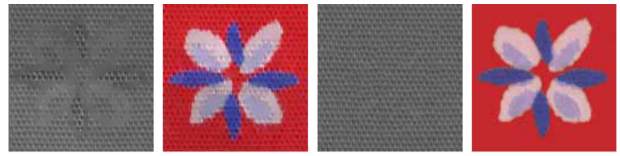
where $p^* \in N(p)$ and $q^* \in N(q)$ are the neighboring pixels of p and q, respectively.

Based on the recovered shading and the original image, the reflectance $\tilde{\rho}_c(p)$ can be easily computed. In practice, as the previous shading adjustment may induce unnecessary spatial variation to the computed reflectance, a further denoising process is applied,



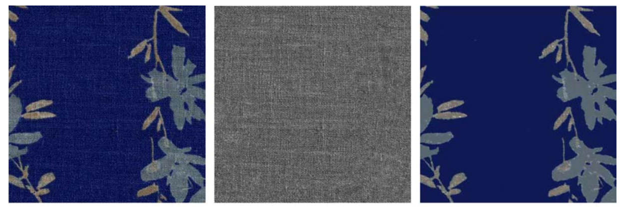
(a) (b)

Fig. 2. (a) Horizontal neighborhood and (b) vertical neighborhood for shading synthesis. The current pixel under processing is indicated by symbol "x."



(a) (b) (c) (d)

Fig. 3. (Color online) (a), (b) Shading and reflectance components recovered by the baseline method. (c), (d) Decomposed shading and reflectance composition by the proposed method.



(a) (b) (c)

Fig. 4. (Color online) (a) Original image is decomposed into the (b) shading component and (c) reflectance component by the proposed method.

$$\tilde{\rho}_c(p) = f_{\mathrm{NL}}(I_c(p)/\tilde{\alpha}(p)), \qquad (8)$$

where the function $f_{\mathrm{NL}}(\cdot)$ represents the noise filtering operator. In this Letter, we use the nonlocal filtering technique for its good denoising capability [6].

In the experiment, various texture images are used to evaluate the proposed method. The representative color of each region is obtained by manually selecting seed pixels and calculating their average color. A classical baseline method is employed for comparison purposes. The baseline method identifies material variation boundaries, zeros the derivatives of the boundary pixels, and then integrates the derivatives to obtain the shading image [2]. Figure 3 shows the results of the two methods in the enlarged area. It is observed that, owing to zeroing derivates, the shading in the boundary is almost flat, and the recovered reflectance still contains obvious shading information in the baseline method. In comparison, the decomposed shading of the proposed method is continuous and uniform, and the recovered reflectance contains much less shading variations. Figure 4 shows the decomposition results of another image with a different texture structure and color pattern. Again, the proposed method produces satisfactory results.

In summary, this Letter proposes a novel method to decompose shading and reflectance components from a single texture image. Each pixel is classified into a region or labeled as ambiguous. The shadings of the definitely classified pixels are computed with respect to the dominant colors, and the ambiguous and boundary pixels are generated using a shading synthesis technique. The reflectance component is computed from the original image and the recovered shading with additional nonlocal denoising. The proposed work is of potential application in texture simulation and image content analysis.

This work was supported by the National Natural Science Foundation of China (NSFC) under grants 60602027 and 60778050.

References

1. M. F. Tappen, W. T. Freemam, and E. H. Adelson, IEEE Trans. Pattern Anal. Mach. Intell. **27**, 1459 (2005).
2. B. V. Funt, M. S. Drew, and M. Brockington, in *Lecture Notes in Computer Science* (Springer-Verlag, 1992), Vol. 588, p. 124.
3. W. H. Press, S. A. Teukolsky, T. T. Vetterling, and B. P. Flannery, *Numerical Recipes in C: The Art of Scientific Computing*, 2nd ed. (Cambridge U. Press, 1992).
4. X. Lu, Opt. Eng. (Bellingham) **46**, 087002 (2007).
5. M. Ashikhmin, in *Proceedings of the 2001 Symposium on Interactive 3D Graphics* (ACM, 2001), p. 217.
6. A. Buades, B. Coll, and J. M. Morel, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (IEEE, 2005), p. 60.