IMAGE DECOMPOSITION USING DECONVOLUTION

Sunghyun Cho, Hyunjun Lee, Seungyong Lee

POSTECH

ABSTRACT

We present a novel method for decomposing an image into base and texture layers. Our method is simple and effective, and can handle textures of high contrast, which traditional image filtering techniques may not handle efficiently. The method first removes high-frequency texture information using low-pass filtering, and then restores structural information of the image using a deconvolution operation. Experimental results demonstrate the effectiveness of our method.

Index Terms— texture layer, image decomposition, image filtering

1. INTRODUCTION

An image can be decomposed into base and texture layers. A base layer consists of smoothly varying regions, and conveys large-scale structural information of an image. A texture layer depicts small-scale variations, and contains details of image appearance. Since these two layers provide different types of information, image decomposition helps solving many kinds of problems in computer vision and graphics, e.g., segmentation, object matching, and non-photorealistic image abstraction.

In spite of its benefits, decomposing an image into base and texture layers is still a challenging problem. It is under-constrained as the number of unknowns is twice the number of pixels. Distinguishing image structures from details is inherently an ambiguous task.

In this paper, we present a simple and effective method for decomposing an image into base and texture layers. The key insight of our method is that low-pass filters can effectively remove textures. Texture can be defined as small-scale oscillating patterns and local variations of image intensities. Under this definition, textures intrinsically correspond to high-frequency components of an image, which can be easily removed using a low-pass filter, e.g., a Gaussian filter.

However, applying a low-pass filter to an image also blurs structural information, such as edges and region boundaries. To recover these structural information, we perform deconvolution on the low-pass filtered image. The deconvolution operation can restore the boundaries between regions of different textures because such information still remains in the blurred image although it has been tampered. On the other hand, high-frequency texture components have been completely lost by the low-pass filtering and are not restored during the deconvolution. The deconvolution result provides the base layer, while the texture layer can be obtained by subtracting the base layer from the given image.

Our method can handle textures of high contrast effectively, while preserving boundaries between regions of different textures. It is simple and fast, consisting of simple low pass filtering and deconvolution steps. Both steps run fast and are easy to implement with plenty of resources including source codes available on internet.

1.1. Related Work

Bilateral filters [1] and feature-preserving smoothing operators have been used to decompose an image into base and detail layers [2, 3]. However, textures often have high-contrast edges and bilateral filters are not effective to handle such textures. Farbman et al. [4] introduced a weighted least squares (WLS) based filter, which better preserves multi-scale features than bilateral filtering. However, their method cannot smooth out textures of high contrast, similarly to bilateral filters.

Besides filtering based techniques, total variation (TV) minimization based techniques have been developed for image decomposition. Rudin et al. [5] introduced a TV minimization based texture removal method. Vese and Osher [6] extended it using the space of oscillating functions introduced by Meyer [7]. Yin et al. [8] used an $L1$-norm fidelity term with total variation regularization to decompose an image into base and texture layers. However, these methods produce quantization artifacts or do not completely remove textures from a base layer (Sec. 3).

In the sense of “blur-and-deconvolve”, filtering by reconstruction technique is similar to ours. It first creates a marker image by applying a low-path filter then reconstruct the image. Maragos and Evangelopoulos [9] proposed a multiscale leveling based technique. Wilkinson showed interesting results by applying levelings with reconstruction criteria [10].

This work was supported by the IT R&D program of MKE/MCST/KEIT (2008-F-031-01, Development of Computational Photography Technologies for Image and Video Contents) and the ERC Program of MEST/NRF (R11-2008-007-01002-3).

Fig. 1: Result of low-pass filtering. Left: source image, right: low-pass filtering result.

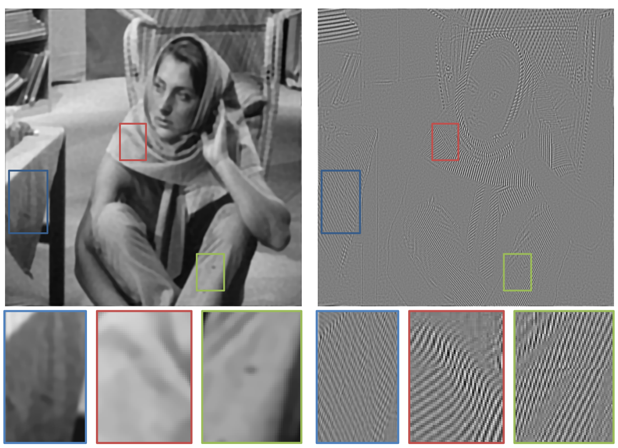


Fig. 2: Result of deconvolution. Left: base layer (deconvolution result), right: texture layer (difference between the source image and the base layer).

2. IMAGE DECOMPOSITION

An image f can be modeled as

$$f(x, y) \quad = \quad b(x, y) + t(x, y), \tag{1}$$

where b and t are base and texture layers, respectively, and x and y are pixel coordinates. Then, the decomposition problem becomes to find b and t from a given f.

A base layer b consists of smoothly varying regions and sharp region boundaries. b describes structural information of an image, such as regions with different textures and shading. A texture layer t contains small-scale oscillating patterns and local intensity variations. t represents the deviations from smoothly varying intensities in local textured regions, and we can assume the average of pixel intensities in a local neighborhood of t is close to zero.

As textures correspond to high-frequency components of an image, a low-pass filter can remove textures with different contrasts and gradient magnitudes (Fig. 1). More specifically, by convolving f with a Gaussian filter g, we obtain a blurred image h as follows:

$$h = f * g = b * g + t * g, \tag{2}$$

where $*$ is the convolution operator. Pixel coordinates are omitted for brevity. Since t contains only high-frequency deviations from local average intensities, it may hold that $t * g \approx 0$. Consequently, h satisfies the following equation:

$$h \quad \approx \quad b * g. \tag{3}$$

The size and standard deviation σ of a Gaussian filter g can be controlled by a user according to the scales of textures.

While a Gaussian filter g removes texture information t effectively, it also blurs structural information such as edges and boundaries between different textures. To restore blurred structural information, we apply a non-blind deconvolution operation to b with a blur kernel g, which solves

$$b' \quad = \quad \arg\min_b \|h - b * g\|^2 + \lambda\rho(b). \tag{4}$$

The first and second terms on the right hand side of Eq. (4) are data fidelity and regularization terms, respectively. λ is a regularization weight, and $\rho(b)$ is a regularization functional of b. For deconvolution, we adopted a fast TV deconvolution method of Wang et al. [11], which effectively restores images with smoothly varying regions and discontinuities.

The recovered b' corresponds to a base layer. It contains smoothly varying regions and sharp edges, but no textures (Fig. 2). A texture layer t is obtained by computing the difference between the source image f and the base layer b'.

Algorithm 1 summarizes the overall process of our decomposition method. The pseudocode shows that our method is simple and easy to implement.

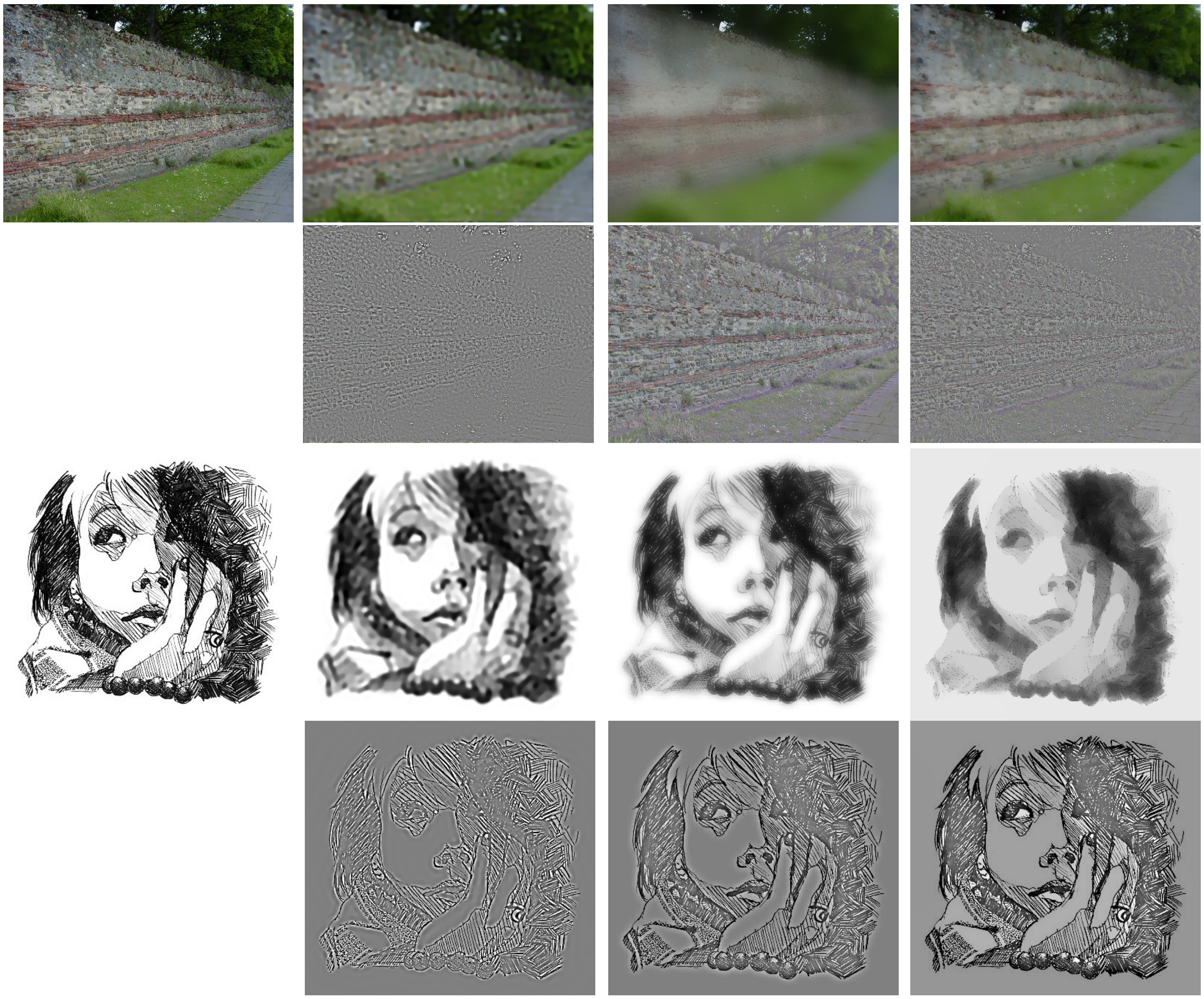
Algorithm 1 Image decomposition

procedure DECOMPOSEIMAGE(f, σ)
  \# σ : standard deviation of a Gaussian filter g
  $g \leftarrow Make\_Gaussian\_Filter(\sigma)$
  $h \leftarrow f * g$
  $b \leftarrow Deconvolve(h, g)$
  $t \leftarrow f - b$
  return b, t
end procedure

3. EXPERIMENTS

Fig. 3 shows decomposition results with different values of the standard deviation σ of a Gaussian filter g. As σ increases, more textures are removed from the base layer.

Fig. 4 compares results of a bilateral filter, a WLS filter [4], and our method. Both input images have high-contrast textures, which cannot be effectively handled by bilateral filters and WLS filters. Due to such high-contrast textures, base



Input image | Our method | Bilateral filter | WLS filter

Fig. 4: Comparison of decomposition results between bilateral filtering, WLS filtering, and our method. The first and third rows show the base layers. The second and fourth rows show the texture layers.

layers of bilateral and WLS filtering results still have texture information and their associated texture layers have structural information. On the other hand, our method successfully decomposed input images into base and texture layers.

Fig. 5 compares results of TV minimization based decomposition methods and ours. While texture patterns still remain in the base layer from the method of Vese and Osher [6], our method successfully removed texture patterns from the base layer. The base layer of Yin et al.'s method [8] has lost shading information and contains quantization artifacts, while our result does not suffer from such artifacts.

Fig. 6 shows other decomposition results of our method. As shown in the result images, our method successfully decomposed given images, even though the input images contain various textures.

We measured the processing time to show the computational efficiency of our method. We implemented our method using Matlab. Our testing environment is a PC running MS Windows XP 32 bit version with Intel Core2 Quad CPU 2.66 GHz. For measuring the processing time, we used grayscale versions of input images of Fig. 6. The sizes of the input images are 395×392 and 768×576, and their processing times were 1.67 and 3.69 seconds, respectively. Further acceleration could be made possible by implementing the method using C/C++.

4. DISCUSSION

This paper presented a novel method for decomposing an image into base and texture layers, which can handle textures

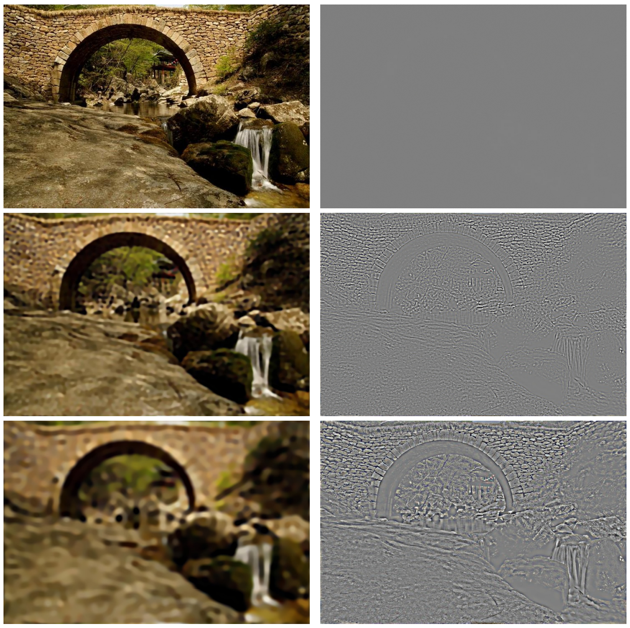


Fig. 3: Decomposition results with different values of the standard deviation σ of a Gaussian filter. Left: base layers, right: texture layers. From top to bottom, σ = 1, 5, and 10.

Our method Vese and Osher [6] Yin et al. [8]

Fig. 5: Comparison of the base layers obtained by TV minimization based methods and ours.

of high contrast effectively. Our method is simple and fast, and easy to implement. We demonstrated its effectiveness by comparing the results with other decomposition methods.

Our method has a limitation, which is caused by low-pass filtering. Because low-pass filters do not remove only textures but also high-frequency structural information, resulting base layers may show blurry edges. Resolving this limitation is our future work. Texture segmentation/classification and multi-scale image decomposition are useful tools for graphics and vision problems. Extending our idea of combining blurring and deconvolution to handle these problems will be interesting future work.

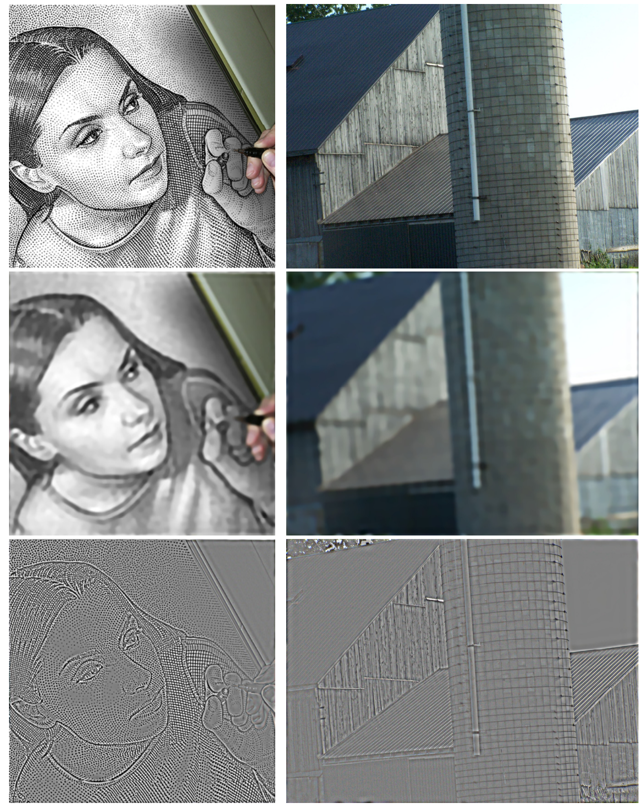


Fig. 6: Other decomposition results. From top to bottom, input images, base layers, and texture layers.

5. REFERENCES

[1] Carlo Tomasi and Roberto Manduchi, "Bilateral filtering for gray and color images," in *Proc. ICCV '98*, 1998, pp. 839–846.

[2] Frédo Durand and Julie Dorsey, "Fast bilateral filtering for the display of high-dynamic-range images," *ACM Trans. Graphics*, vol. 21, no. 3, pp. 257–266, 2002.

[3] Soonmin Bae, Sylvain Paris, and Frédo Durand, "Two-scale tone management for photographic look," *ACM Trans. Graphics*, vol. 25, no. 3, pp. 637–645, 2006.

[4] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, "Edge-preserving decompositions for multi-scale tone and detail manipulation," *ACM Trans. Graphics*, vol. 27, no. 3, pp. article no. 67, 2008.

[5] L. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D*, vol. 60, no. 1-4, pp. 259–268, 1992.

[6] Luminita A. Vese and Stanley J. Osher, "Modeling textures with total variation minimization and oscillating patterns in image processing," *J. Sci. Comput.*, vol. 19, no. 1-3, pp. 553–572, 2003.

[7] Yves Meyer, *Oscillating Patterns in Image Processing and Nonlinear Evolution Equations: The Fifteenth Dean Jacqueline B. Lewis Memorial Lectures*, American Mathematical Society, Boston, MA, USA, 2001.

[8] W. Yin, D. Goldfarb, and S. Osher, "Image cartoon-texture decomposition and feature selection using the total variation regularized l1 functional," *Variational, Geometric, and Level Set Methods in Computer Vision*, vol. 3752, pp. 73–84, 2005.

[9] Petros Maragos and Georgios Evangelopoulos, "Leveling cartoons, texture energy markers, and image decomposition," in *Proc. International Symposium on Mathematical Morphology*, 2007, vol. 1, pp. 125–138.

[10] Michael H.F. Wilkinson, "Connected filtering by reconstruction: basis and new advances," in *Proc. ICIP 2008*, 2008, pp. 2180–2183.

[11] Yilun Wang, Junfeng Yang, Wotao Yin, and Yin Zhang, "A new alternating minimization algorithm for total variation image reconstruction," *SIAM Journal on Imaging Sciences*, vol. 1, no. 3, pp. 248–272, 2008.