Visual Comput (2007) 23: 641–650
DOI 10.1007/s00371-007-0155-2

ORIGINAL ARTICLE

**Jianbing Shen**
**Xiaogang Jin**
**Hanqiu Sun**

# High dynamic range image tone mapping and retexturing using fast trilateral filtering

Published online: 5 July 2007


J. Shen · X. Jin (✉)
State Key Lab of CAD & CG,
Zhejiang University, Hangzhou, 310027,
P.R. China
{shenjianbing, jin}@cad.zju.edu.cn

H. Sun
Department of Computer Science and Engineering, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong
hanqiu@cse.cuhk.edu.hk

**Abstract** Using fast trilateral filtering we present a novel tone mapping and retexturing method for high dynamic range (HDR) images. Our new trilateral filtering-based tone mapping is about seven to ten times faster than that in [3]. Firstly, a novel tone mapping algorithm for HDR images is presented. It is based on fast bilateral filtering and two newly developed filters: the quasi-Cauchy function kernel filter and the fourth degree Taylor polynomial kernel filter. Secondly, a new gradient-based image retexturing method is introduced, which consists of three steps: 1) converting HDR images into low dynamic range (LDR) images using our fast trilateral filtering-based tone mapping method; 2) recovering the gradient luminance maps for the region to be retextured; 3) reconstructing the final retextured image by solving the Poisson equation. The proposed approach is suitable for HDR image tone mapping and retexturing, and experimental results have demonstrated the satisfactory performance of our method.

**Keywords** High dynamic range image · Fast trilateral filtering · Tone mapping · Retexturing

## 1 Introduction

In recent years, high dynamic range (HDR) imaging and processing is becoming more and more popular in topics including HDR image acquisition [4], tone mapping [3, 6, 9, 18, 24, 30], displaying systems [27], and other applications [2, 12, 19, 26]. An HDR image can accurately capture the entire range of luminance in most natural scenes whereas the traditional low dynamic range (LDR) image stores only a fraction of the range of luminance encountered in the real world with some particular precision. The dominant display technologies (such as CRTs and LCDs) have limited dynamic ranges. Therefore, HDR image tone mapping [3, 6, 9, 13, 24, 30] techniques have been developed for compressing the dynamic range of the data. Ideally, the tone mapping techniques should work automatically and be easy to implement without introducing unpleasant artifacts. The trilateral filter-based HDR tone mapping technique [3] proposed by Choudhury et al. is one of the best developed techniques for compressing the dynamic range. This method can preserve edges and smooth high-gradient regions. However, the main limitation of Choudhury et al.'s method lies in its high computational cost, as processing an HDR image needs several minutes. Thus, it is necessary to develop a novel HDR tone mapping using fast trilateral filtering.

Image re-texturing is a process to replace existing textures in a region of an image by new textures while preserving the original shading effects. Although there are some LDR image retexturing methods in the literature [7, 8, 10, 32, 34], few of them retexture HDR images. Recently, Khan et al. [12] presented a novel image-based material editing method for making objects transparent and translucent, which allows to retexturing of the HDR images. However, their scheme is slow since it needs a time-consuming bilateral filtering process. Besides, their method requires HDR images when retexturing. Therefore, it is necessary to develop an efficient retexturing algorithm for both LDR and HDR images.

In this paper, we first present a new trilateral filtering algorithm, which is sufficiently fast for tone mapping with HDR images. After that, we develop a novel trilateral filtering-based image retexturing method in the gradient domain for both HDR and LDR images. Our retexturing method consists of three major steps: 1) converting HDR images into LDR images using our fast trilateral filtering-based tone mapping method, 2) recovering the gradient depth maps for the region to be re-textured, and 3) reconstructing the final re-textured image by solving a Poisson equation. As demonstrated later, our tone-mapping and retexturing methods can produce similar image quality with the proposed method in [8, 12] in a comparable computing time.

Our approach has three contributions:

– Two novel fast filters, a quasi-Cauchy function kernel filter and a fourth degree Taylor polynomial kernel filter, are developed.
– A new HDR tone mapping algorithm using fast trilateral filtering is introduced, which is about seven to ten times faster than the trilateral filtering method in [3].
– A unified framework for retexturing HDR and LDR images in the gradient domain is proposed, which integrates the techniques of high-dynamic range image tone mapping, image retexturing, and gradient-based image processing.

## 2 Related work

Tone mapping operators

Many different tone mapping operators have been proposed in the computer graphics and image processing literature over the years. We refer the reader to [25] for a survey of these methods. Tone mapping operators [3, 6, 9, 14, 16] can be roughly classified into global and local (spatially variant) techniques. Most global techniques [5, 23] do not directly address contrast reduction because they use the same mapping function for all pixels. Most of the local operators [3, 6, 9] compute the local adaptation luminance by finding the arithmetic mean of the pixel luminance in a local neighborhood. Fattal et al. [9] computed a gain map for the gradient of an image so as to reduce large gradients to small ones, and then solved Poisson's equation to retrieve an image within the compressed range. These operators invariably produce halo artifacts around regions of high contrast. Lischinski et al. [16] proposed an interactive local adjustment method. In their method, the user first indicates the regions of interest by drawing a few simple brush strokes, then the system adjusts the brightness, contrast and other parameters in these regions automatically.

Most recent operators [3, 5, 6, 9, 14, 16] can effectively map HDR radiance maps into displayable LDR images. However, local operators sometimes introduce visual artifacts into the tone mapped result. As a visual detail-removing filter [6, 31], the bilateral filter has serious drawbacks. Therefore, Choudhury et al. [3] presented a novel trilateral filter-based tone mapping method for HDR images. The method needs several minutes to process an HDR image, which is time-consuming [3]. Based on a novel trilateral filtering, we present a fast tone mapping operator for HDR images. Our proposed method is based on a recent fast bilateral filtering technique [21] and our two newly developed fast kernel filters: the quasi-Cauchy function and the fourth degree Taylor polynomial function.

Image retexturing

Texture replacement techniques have been fascinating for a long time. Many image retexturing methods have been developed. For instance, Oh et al. [20] introduced a technique to change the shape, color and illumination of objects depicted in images. Liu et al. [17] demonstrated a user-assisted adjustment on the regular grid of the real texture and obtained a bijective mapping between the regular grid of the texture and the deformed grid of the surface image. Obviously, their method requires elaborate user interactions and is only suitable for regular textures. Fang and Hart [7, 8] proposed an efficient object retexturing technique. Their method is based on the assumption that the lighting satisfies the Lambertian reflectance model, and the object's macro structure can be altered [7]. Guo et al. [10] proposed a novel image and video retexturing approach that preserves the original shading effects without knowledge of the underlying surface and lighting conditions. All the above retexturing techniques focus on LDR rather than HDR images.

An existing approach that is the most relevant to ours is Khan's image-based material editing technique, which focuses on the variation of the object's microstructure that would normally be modeled with functions such as bi-directional reflectance distribution functions (BRDFs). Given a single HDR photograph, their method achieves visually pleasing results when changing the material properties of objects. However, their method operates on the input HDR images directly, which is time-consuming in the process of bilateral filtering. Another limitation is that their method assumes that the input image is given as a high dynamic range image, and it is not effective for retexturing an LDR image.

## 3 Our approach

### 3.1 Fast quasi-Cauchy and Taylor polynomial kernel filters

The weight functions used by [3, 31] are standard Gaussian filters. Letting $x = t/\sigma$ the Gaussian filter is

$$G(x) = \exp(-x^2/2). \quad (1)$$

If we take $x^2$ as the input, the floating operations involved are one exponent operation, one division operation and one minus operation. The exponent operation in the Gaussian function is computationally expensive. We try to approximate the Gaussian filter by other functions that do not involve any exponent floating operations. In this paper, we present two candidate functions: the quasi-Cauchy kernel and the Taylor polynomial expansion of the Gaussian kernel.

Quasi-Cauchy function originates from the Cauchy distribution function $1/(\pi(1+x^2))$. Sherstyuk [29] refined it to approximate the shape of the Gaussian function more tightly. He called the resulting function the *quasi-Cauchy* function, which is given by

$$G(x) = 1/(1+s^2x^2)^2, \quad (2)$$

where $s$ is a parameter to adjust the width of the kernel. This quasi-Cauchy function is a very useful filter kernel in analytical convolution surface modeling [11, 29].

The integral over $(-\infty, +\infty)$ for the Gaussian filter is

$$\int_{-\infty}^{+\infty} e^{-x^2/2}\mathrm{d}x = \sqrt{2\pi} \quad (3)$$

and the integral over $(-\infty, +\infty)$ for the quasi-Cauchy function is

$$\int_{-\infty}^{+\infty} 1/(1+s^2x^2)^2\mathrm{d}x = \pi/(2s). \quad (4)$$

To make these two integrals equal, we set $s^2 = \pi/8$ and obtain

$$G(x) = 64/(8+\pi x^2)^2. \quad (5)$$

Let $A = 8/\pi$ and $B = A^2 = 64/\pi^2$, Eq. 5 can be further reduced to

$$G(x) = B/(A+x^2)^2 \quad (6)$$

with one multiplication operation, one division operation and one plus operation.

Alternatively, we can also approximate the Gaussian filter by the fourth degree Taylor polynomial at zero as

$$G(x) = 1/(1+x^2/2+x^4/8+x^6/48+x^8/384). \quad (7)$$

In order to reduce the computation, we reformulate it to the form

$$G(x) = 384/(384+x^2\times(192+x^2\times(48+x^2\times(8+x^2)))). \quad (8)$$

The evaluation of $G(x)$ in this form involves three multiplication operations, one division operation and four plus operations. Table 1 summarizes the special functions and floating point operations involved for three kernels.

From the plotted curves in Fig. 1, we can see that the fourth degree Taylor polynomial filter is very close to the Gaussian function, while the quasi-Cauchy filter is slightly narrower than the Gaussian function with slower convergence.

### 3.2 Tone mapping using fast trilateral filtering

The existing trilateral filter combines two modified gradient bilateral filters with a novel image-stack scheme for fast region-finding [3]. However, the computation involved in the bilateral filtering is very time consuming. The key problem for accelerating the trilateral filtering is to improve the speed of the gradient bilateral filtering. Based on the quasi-Cauchy function or the fourth degree Taylor polynomial kernel filter, we present our fast trilateral filtering combining with Paris et al.'s [21] fast bilateral filtering.

With the fast quasi-Cauchy function filter or the fourth degree Taylor polynomial filter that we developed in Sect. 3.1, the gradient bilateral filter of image $I$ at the pixel $p$ is defined by

$$\nabla I^{\mathrm{bf}} = \frac{1}{k}\sum_{q\in I} G\sigma_s(\|p-q\|)G\sigma_r(\|\nabla I_p - \nabla I_q\|)\nabla I_p \quad (9)$$

$$k = \sum_{q\in I} G\sigma_s(\|p-q\|)G\sigma_r(\|\nabla I_p - \nabla I_q\|), \quad (10)$$

where $\nabla I$ denotes the gradient of image $I$, $\sigma_s$ controls the spatial neighborhood, $\sigma_r$ controls the influence of the intensity difference, and $G\sigma_r(\cdot)$ and $G\sigma_s(\cdot)$ are the kernels

**Table 1.** Special functions and floating-point operations for three different kernels

| Kernel function | exp | × | / | + | − |
|---|---|---|---|---|---|
| Quasi-Cauchy | | 1 | 1 | 1 | |
| Taylor polynomial | | 3 | 1 | 4 | |
| Gaussian | 1 | | 1 | | 1 |

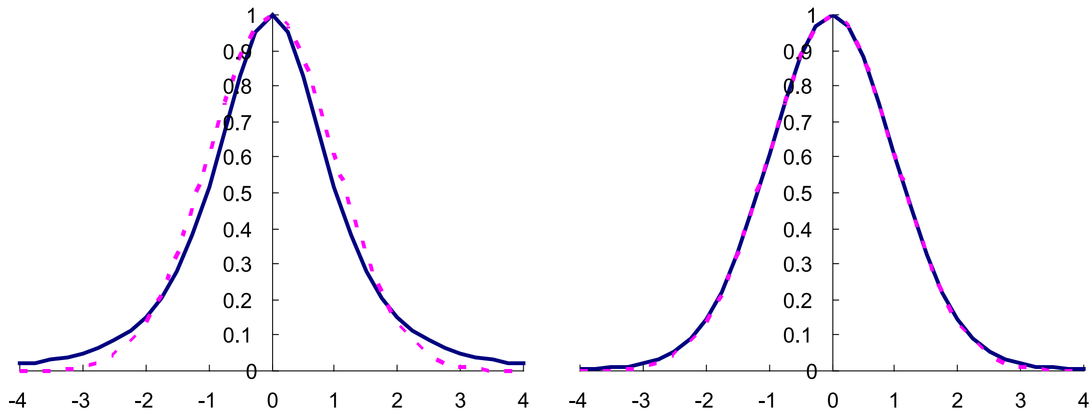



**Fig. 1a,b.** Plotted function. **a** Quasi-Cauchy function (*solid line*) vs. Gaussian function (*dashed line*). **b** Fourth degree Taylor polynomial (*solid line*) vs. Gaussian function (*dashed line*)

in the form of the quasi-Cauchy function or the fourth degree Taylor polynomial function.

To keep the property that the bilateral filter is a weighted average, we rewrite Eq. 9 by introducing a function $W$ using two-dimensional vectors

$$\begin{pmatrix} W_p^{\mathrm{bf}} \nabla I_p^{\mathrm{bf}} \\ W_p^{\mathrm{bf}} \end{pmatrix} = \sum_{q \in I} G\sigma_s(\|p-q\|) G\sigma_r(\|\nabla I_p - \nabla I_q\|) \begin{pmatrix} W_q \nabla I_q \\ W_q \end{pmatrix}. \quad (11)$$

According to the above equation, the functions $i^{\mathrm{bf}}$ and $w^{\mathrm{bf}}$ are introduced to express the gradient bilateral filter as a convolution followed by nonlinear operations

$$(w^{\mathrm{bf}} i^{\mathrm{bf}}, w^{\mathrm{bf}}) = g_{\sigma_s, \sigma_r} \otimes (w_i, w), \quad (12)$$

$$\nabla I_p^{\mathrm{bf}} = \frac{w^{\mathrm{bf}}(p, \nabla I_p) i^{\mathrm{bf}}(p, \nabla I_p)}{w^{\mathrm{bf}}(p, \nabla I_p)}. \quad (13)$$

Firstly, our trilateral filter uses two aforementioned fast gradient bilateral filters and a min-max image stack, which achieves the *edge-limited smoothing* effect offered by the shocks that form in the anisotropic diffusion. Then we apply a threshold to form a binary signal that limits the smoothed neighborhood to the connected regions that share similar $\|\nabla I^{\mathrm{bf}}\|$ as in [3]. Finally, only one user-specified parameter $\sigma_{c\theta}$ [3] is required to avoid hand-tuned parameters and to improve the usefulness and generality of the fast trilateral filtering for HDR image tone mapping.

## 4 Image retexturing based on fast trilateral filtering

The image retexturing algorithm using fast trilateral filtering consists of eight steps, which are outlined as follows:

1. Input: an LDR image $I_L$ or an HDR image $I_H$.
2. If the input image is an HDR image, we apply our fast trilateral filtering on the HDR image $I_H$ to get the tone mapping LDR image $I_{\mathrm{in}} = FT(I_H)$. Otherwise, just set $I_{\mathrm{in}} = I_L$.
3. Computing the luminance image of each pixel in $I_{in}$ to get an initial depth map by $I_d(x, y) = I_L(x, y) = 0.213R(x, y) + 0.715G(x, y) + 0.072B(x, y)$.
4. The fast trilateral filtering method is used again to filter the depth image to get a smooth depth map image $I_d^s = FT(I_d)$.
5. Evaluating the gradient depth map: $\nabla I_G(x, y) = (I_d^s(x+1, y) - I_d^s(x, y), I_d^s(x, y+1) - I_d^s(x, y))$.
6. Computing the texture indices $[t_x, t_y]$ according to the gradient depth map $\nabla I_G(x, y)$.
7. Deriving the new color gradient $\nabla I'_G(x, y)$ from its original color gradient and the input texture image gradient $\nabla T_G(t_x, t_y)$.
8. Reconstructing the final retextured image $I'$ from $\nabla I'_G(x, y)$ by solving a Poisson equation.

### 4.1 Gradient depth recovery

As the shape from shading problem is a severely under-constrained problem [35], there are generally no good solutions to calculate a depth map from a single image. Therefore, our approach focuses on deriving a locally-consistent depth-map from the object's luminance distribution, where high luminance values specify the parts of the object closer to the observer. Similarly to [12], an initial depth map $I_d(x, y)$ is computed by

$$I_d(x, y) = I_L(x, y), \quad (14)$$

$$I_L(x, y) = 0.213R(x, y) + 0.715G(x, y) + 0.072B(x, y). \quad (15)$$

After that, we use our fast trilateral filtering to smooth the initial depth map $I_d^s = FT(I_d)$. The filtered depth map can then be used to estimate the local gradient map. The final recovered gradient depth field $I_G(x, y)$ is defined in terms of neighboring depth values, as follows

$$\nabla I_G(x, y), \\ = \left(I_d^s(x+1, y) - I_d^s(x, y), I_d^s(x, y+1) - I_d^s(x, y)\right). \quad (16)$$

The resultant gradient field can be applied directly to warp textures to achieve the object's retexturing.

It is obvious that this approach has some problems such as errors of the retextured object in the depth map. However, the gross inaccuracies of the gradient depth maps in shape reconstruction do not interfere with the visual effect for our application.

### 4.2 Image retexturing

In general, the gradient field $\nabla I_G$ is sufficient to be used to estimate the warping of an arbitrary texture image $T$, which can be applied to retexture the object. Here, we use the lazy snapping technique [15] to segment the object to be retextured. Unlike [12], two nonlinear gradient scale factors $(1 + \|\nabla_x I_G\|)$ and $(1 + \|\nabla_y I_G\|)$ areintroduced to calculate the texture indices $[t_x, t_y]$ by

$$t_x = (1 + \|\nabla_x I_G\|) * \nabla_x I_G, t_y = (1 + \|\nabla_y I_G\|) * \nabla_y I_G. \quad (17)$$

Assuming that a pixel $[x, y]$ belonging to the object has an RGB color gradient triplet denoted $\nabla I_G(x, y)$, we can derive the new color gradient $\nabla I'_G(x, y)$ from its original color gradient and the input texture image gradient $\nabla T_G(t_x, t_y)$ as the following matting equation:

$$\nabla I'_G(x, y) = (1 - f) * f * \nabla T_G(t_x, t_y) + f * \nabla I_G(x, y), \quad (18)$$

where $f$ is the scalar parameter that linearly interpolates the original object's color gradient and the texture mapped color gradient [12].

After obtaining the re-textured gradient maps $\nabla I'_G$, we can reconstruct the final re-texturing image $I'$ by solving a Poisson equation. Let $I'$ denote the image that is to be reconstructed from $G'$; one of the methods recently proposed in [9] determines $I'$ by minimizing $\|\nabla I' - \nabla I'_G\|$. By introducing a divergence and a Laplacian operator, we can build $I'$ by solving the Poisson equation $\nabla^2 I' = \mathrm{div}([\nabla I'_{Gx}, \nabla I'_{Gy}])$ [1, 9, 22, 28]. Two results with $f = 0.5$ are shown in Fig. 5, which illustrate that our approach is capable of reproducing both Fang's result [8] and Khan's result [12].

## 5 Experimental results and discussions

We have applied our proposed algorithm to a variety of high dynamic range (HDR) images. The experimental results demonstrated that visually pleasing tone mapping and retexturing images can be generated by our approach. All the examples shown in this section were tested on a PC with Pentium IV 1.6 GHz CPU + 512 MB RAM.

As pointed out in [3], the trilateral filter offers several notable improvements when used for high dynamic range (HDR) image tone mapping. Several HDR source images collected from previously published papers on tone mapping [3, 5, 6, 9, 14] have been processed by our fast trilateral filtering-based tone mapping for contrast reduction. The experimental results showed that our approach is capable of reproducing Choudhury's [3] tone mapping results, and about seven to ten times faster than theirs. The computational time statistics of our method are listed in Table 2.

Figures 2 and 4 show that our fast trilateral filtering-based tone mapping is particularly good at edge-preserved smoothing in the large gradient regions of an image, such as the inner ring of the skylight (Fig. 2a). Note the texture of the stained glass is very rich (Fig. 2b, d, f) and the contrast on the desktop is pronounced (Fig. 2b). The appearance of the sky (Fig. 2j, k, l), the mountains (Fig. 4b), and the green meadow (Fig. 2l, Fig. 4a) is also greatly enhanced by our method. Our approach also avoids blooming effects that enlarge, blur or brighten large gradient neighborhoods, such as the ring-like specular highlight (Fig. 2d). Figure 4 illustrates more challenging photographic situations, such as the ability of our fast trilateral filtering-based tone mapping to preserve large features with sharp gradients (Fig. 4d–g). Our technique has the ability to achieve the overall pleasing photo-realistic appearance while preserving fine details.

Figure 3 compares our tone mapping result (Fig. 3a) with the ones published by Durand and Dorsey [6] (Fig. 3b), Fattal et al. [9] (Fig. 3c) and Drago et al. [5] (Fig. 3d). All the methods give visually pleasing results in making detail visible in both the bright and dark regions,

**Table 2.** Computational statistics

| Examples | Memorial | Rosette | Desk | Tree | StillLife | Cathedral |
|---|---|---|---|---|---|---|
| Image size | $512 \times 768$ | $720 \times 480$ | $644 \times 874$ | $928 \times 906$ | $1240 \times 846$ | $1023 \times 767$ |
| Time of [3] in seconds | 130 625 | 122 906 | 211 809 | 286 843 | 361 078 | 285 187 |
| Our time in seconds | 12 781 | 17 015 | 29 875 | 36 421 | 46 171 | 36 531 |

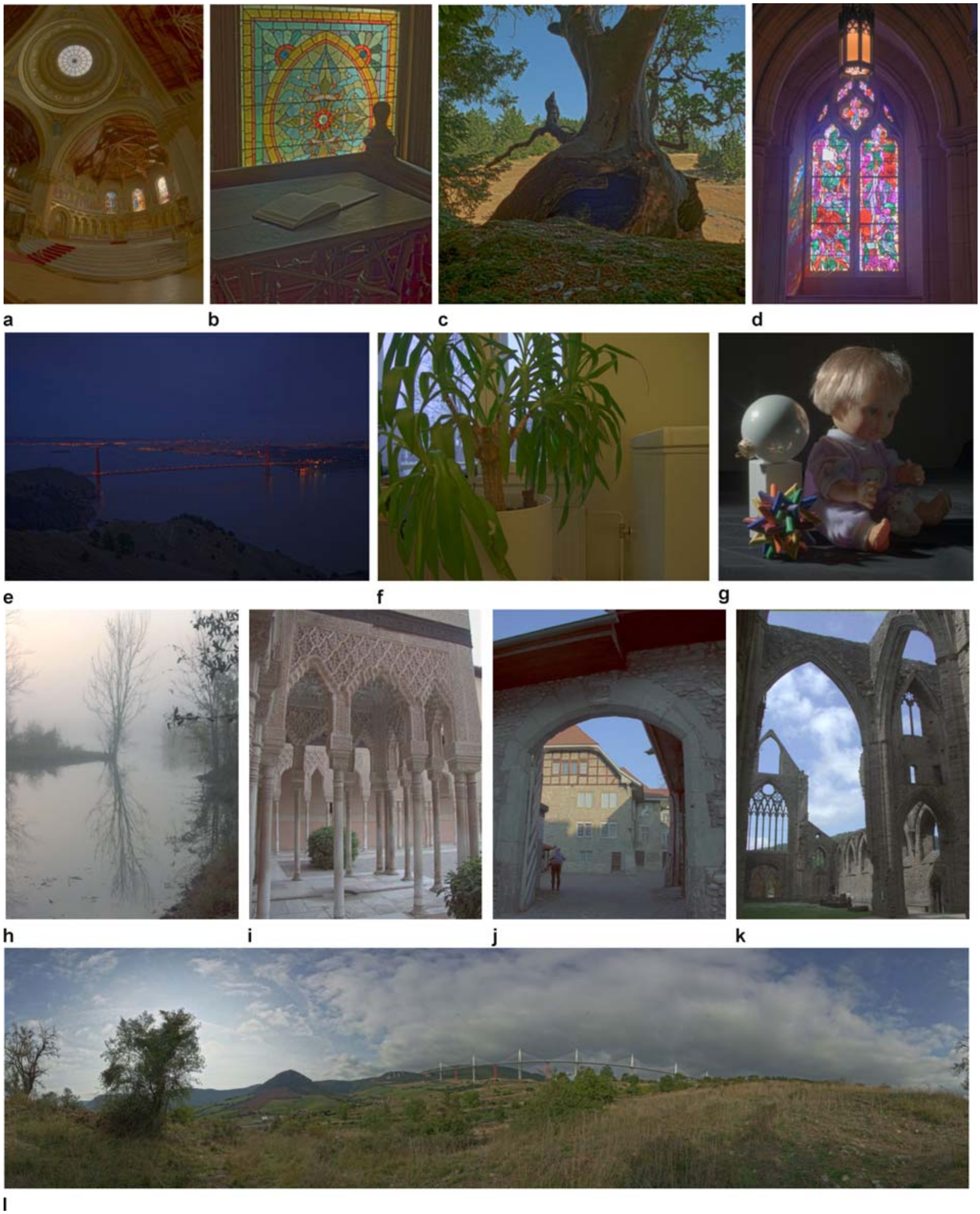


**Fig. 2a–l.** Examples of high dynamic range tone mapping using our fast trilateral filtering: **a** Stanford Memorial Church (courtesy of Paul Debevec, University of Southern California), **b** desk and **c** tree (courtesy of Industrial Light & Magic), **d** Washington DC Cathedral (courtesy of Max Lyons), **e** Golden Gate (courtesy of OpenEXR, http://www.openexr.com), **f** yucca (courtesy of Kimmo Roimela, Nokia Research Center), **g** doll (courtesy of Yuanzhen Li [14]), **h** foggy, **i** Alhambra, **j** courtyard and **k** Tintern Abbey (courtesy of Erik Reinhard, University of Central Florida), and **l** Viaduc (courtesy of HDRsoft, http://www.hdrsoft.com)

**Fig. 3a–d.** Grand Canal: **a** result by our tone mapping using fast trilateral filtering, **b** result by Durand and Dorsey [6], **c** result by Fattal et al. [9], **d** result by Drago et al. [5] (courtesy of HDRsoft, *http://www.hdrsoft.com*)

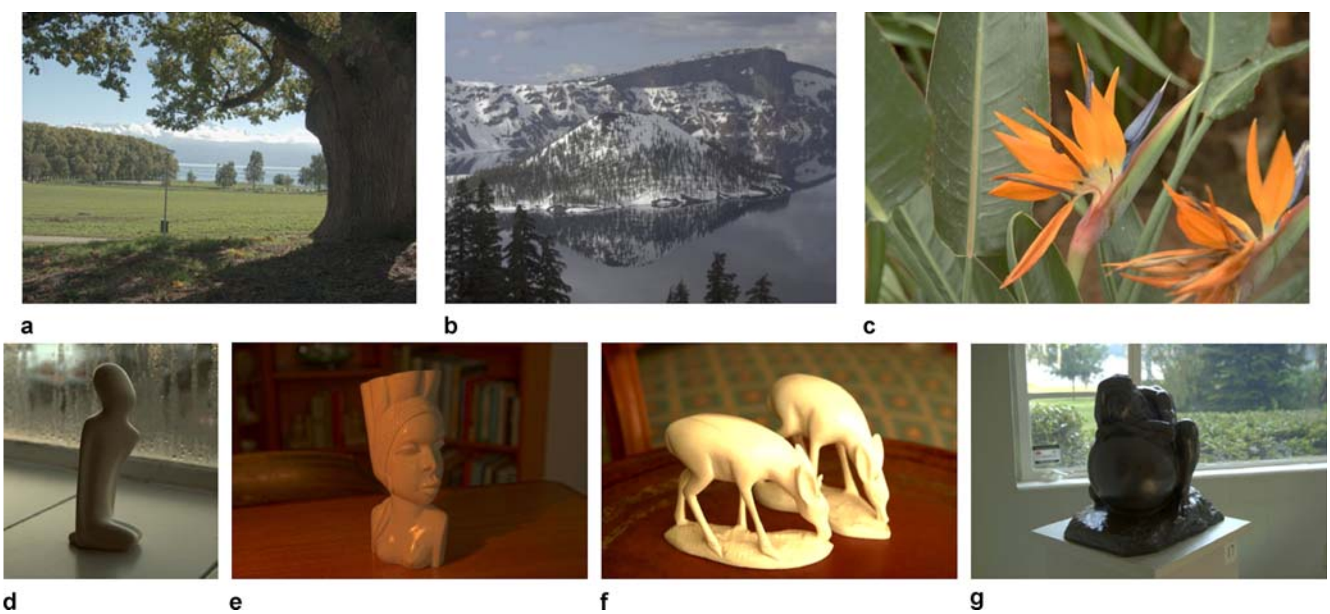


**Fig. 4a–g.** More examples of high dynamic range image tone mapping using our fast trilateral filtering, **a** courtesy of Laurence Meylan [18], **b** and **c** courtesy of Erik Reinhard, University of Central Florida, **d**,**e**,**f** and **g**, courtesy of Erum Arif Khan, University of Central Florida

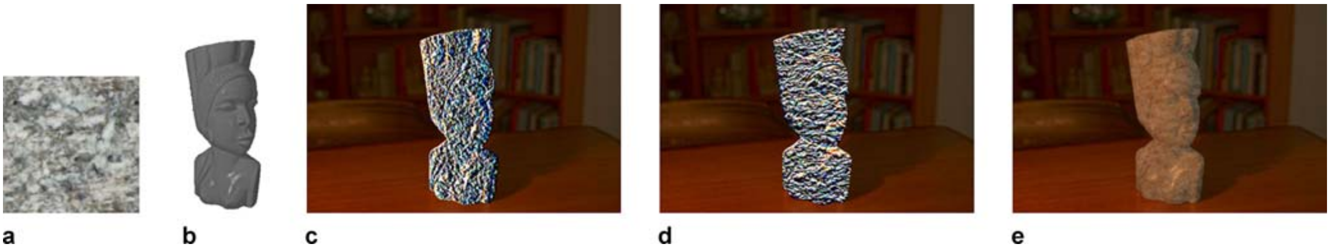



**Fig. 5a–e.** Illustration for our retexturing approach in the gradient domain using fast trilateral filtering: **a** the input marble texture, **b** the depth map after fast trilateral filtering (the object needs to be retextured), **c** and **d** the retextured gradient maps in horizontal and vertical directions, **e** the reconstructed retexturing image

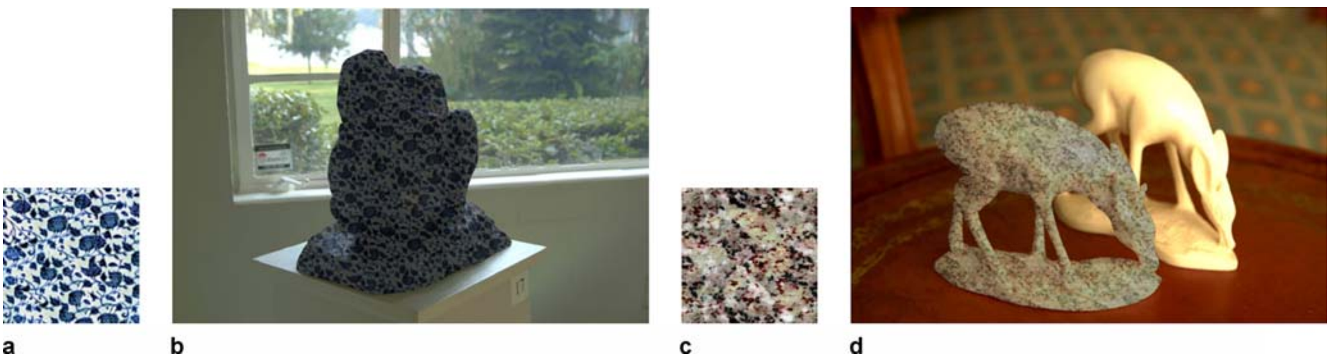



**Fig. 6.** More examples of retexturing results: **a** and **c** input textures, **b** and **d** retexturing results

but some differences exist from the results including overall difference in color, sharpness and detail preserving (Fig. 3a). Since the results may change depending on the details of the implementation, they should not be overinterpreted.

Figures 5 and 6 show the image retexturing results obtained with our newly developed fast trilateral filtering based method in the gradient domain. When we retexture an LDR or HDR image with a marble texture or a stone texture, our approach can reproduce Khan's results [12] according to the recovered gradient depth maps. Additionally, our method is much faster than theirs as we use a fast trilateral filtering-based tone mapping to convert HDR images into LDR ones. Our retexturing method is applied on LDR images in the gradient domain, while Khan's approach is directly applied on HDR images with time-consuming bilateral filtering.

## 6 Conclusions and future work

In this paper, we have proposed a novel tone mapping and retexturing approach for high dynamic range images using our fast trilateral filtering method. Integrating the newly developed fast bilateral filtering and the quasi-Cauchy function kernel or the fourth degree Taylor polynomial kernel, our proposed trilateral filtering based the tone mapping approach is about seven to ten times faster than the existing trilateral filter-based one in [3]. Our retexturing method based on fast trilateral filtering is applied on the gradient domain of LDR images while Khan's method [12] is applied directly on the HDR images. Khan's method involves a time-consuming bilateral filtering process on HDR images, but ours does not. The experimental results demonstrated both the feasibility and the efficiency of our proposed algorithm.

Our future work includes exploring better methods for recovering the gradient depth maps, adopting graphics hardware acceleration [19], and investigating the extension to HDR image compression [26, 33] and interactive video retexturing [7, 10].

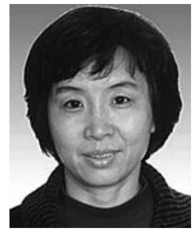
**Acknowledgement** This work was supported by the China 863 program (grant No. 2006AA01Z314), the National Natural Science Foundation of China (grant No. 60573153), the Natural Science Foundation of Zhejiang Province (grant No. R1054-31), and the Program for New Century Excellent Talents in University (grant No. NCET-05-0519). The authors would like to thank Erum Arif Khan for providing his valuable HDR source data and Charlie C.L. Wang for his help in presenting the manuscript.

## References


1. Agrawal, A., Raskar, R., Nayar, S.K., Li, Y.: Removing flash artifacts using gradient analysis. ACM Trans. Graph. **24**(3), 828–835 (2005)
2. Bae, S., Paris, S., Durand, F.: Two-scale tone management for photographic look. ACM Trans. Graph. **25**(3), 637–645 (2006)
3. Choudhury, P., Tumblin, J.: The trilateral filter for high contrast images and meshes. Eurographics Symposium on Rendering ’03, pp. 186–196 (2003)
4. Debevec, P.E., Malik, J.: Recovering high dynamic range radiance maps from photographs. In: Proceedings of SIGGRAPH ’97, pp. 369–378. ACM, New York (1997)
5. Drago, F., Myszkowski, K., Annen, T., Chiba, N.: Adaptive logarithmic mapping for displaying high contrast scenes. Comput. Graph. Forum **22**(3), 419–426 (2003)
6. Durand, F., Dorsey, J.: Fast bilateral filtering for the display of high-dynamic-range images. In: Proceedings of SIGGRAPH ’02, pp. 257–266. ACM, New York (2002)
7. Fang, H., Hart, J.C.: RotoTexture: automated tools for texturing raw video. IEEE Trans. Vis. Comput. Graph. **12**(6), 1580–1589 (2006)
8. Fang, H., Hart, J.C.: Textureshop: texture synthesis as a photograph editing tool. ACM Trans. Graph. **23**(3), 354–359 (2004)
9. Fattal, R., Lischinski, D., Werman, M.: Gradient domain high dynamic range compression. In: Proceedings of SIGGRAPH ’02, pp. 249–256. ACM, New York (2002)
10. Guo, Y.W., Wang, J., Zeng, X., Xie, Z.Y., Sun, H.Q., Peng, Q.S.: Image and video retexturing. Comput. Animation Virtual Worlds **16**, 451–461 (2005)
11. Jin, X.G., Tai, C.L., Feng, J.Q., Peng, Q.S.: Convolution surfaces for line skeletons with polynomial weight distributions. J. Graph. Tools **6**(3), 17–28 (2001)
12. Khan, E.A., Reinhard, E., Fleming, R.W., Bülthoff, H.H.: Image-based material editing. ACM Trans. Graph. **25**(3), 654–663 (2006)
13. Krawczyk, G., Myszkowski, K., Seidel, H.-P.: Lightness perception in tone reproduction for high dynamic range images. Comput. Graph. Forum **24**(3), 635–645 (2005)
14. Li, Y., Sharan, L., Adelson, E.H.: Compressing and companding high dynamic range images with subband architectures. ACM Trans. Graph. **24**(3), 836–844 (2005)
15. Li, Y., Sun, J., Tang, C.-K., Shum, H.-Y.: Lazy snapping. ACM Trans. Graph. **23**(3), 303–308 (2004)
16. Lischinski, D., Farbman, Z., Uyttendaele, M., Szeliski, R.: Interactive local adjustment of tonal values. ACM Trans. Graph. **25**(3), 646–653 (2006)
17. Liu, Y.X., Lin, W.C., Hays, J.: Near regular texture analysis and manipulation. ACM Trans. Graph. **23**(3), 368–376 (2004)
18. Meylan, L., Süsstrunk, S.: High dynamic range image rendering using a retinex-based adaptive filter. IEEE Trans. Image Processing **15**(9), 2820–2830 (2006)
19. Munkberg, J., Clarberg, P., Hasselgren, J., Akenine-Möller, T.: High dynamic range texture compression for graphics hardware. ACM Trans. Graph. **25**(3), 698–706 (2006)
20. Oh, B.M., Chen, M., Dorsey, J., Durand, F.: Image-based modeling and photo editing. In: Proceedings of SIGGRAPH ’01, Los Angeles, pp. 433–442. ACM, New York (2001)
21. Paris, S., Durand, F.: A fast approximation of the bilateral filter using a signal processing approach. In: Proceedings of European Conference on Computer Vision ’06. Graz, Austria, pp. 568–580 (2006)
22. Pérez, P., Gangnet, M., Blake, A.: Poisson image editing. ACM Trans. Graph. **22**(3), 313–318 (2003)
23. Reinhard, E., Devlin, K.: Dynamic range reduction inspired by photoreceptor physiology. IEEE Trans. Vis. Comput. Graph. **11**(1), 13–24 (2005)
24. Reinhard, E., Stark, M., Shirley, P., Ferwerda, J.: Photographic tone reproduction for digital images. In: Proceedings of SIGGRAPH’02, pp. 267–276. ACM, New York (2002)
25. Reinhard, E., Ward, G., Pattanaik, S., Debevec, P.: High dynamic range imaging. Morgan Kaufmann, San Francisco (2006)
26. Roimela, K., Aarnio, T., Itäranta, J.: High dynamic range texture compression, ACM Trans. Graph. **25**(3), 707–712(2006)
27. Seetzen, H., Heidrich, W., Stuerzlinger, W., Ward, G., Whitehead, L., Trentacoste, M., Ghosh, A., Vorozcovs, A.: High dynamic range display systems. ACM Trans. Graph. **23**(3), 760–768 (2004)
28. Shen, J.B., Jin, X.G., Zhou, C., Wang, C.C.L.: Gradient based image completion by solving the Poisson equation. Comput. Graph. **31**(1), 119–126 (2007)
29. Sherstyuk, A.: Kernel functions in convolution surfaces: a comparative analysis. Visual Comput. **15**(4), 171–182 (1999)
30. Smith, K., Krawczyk, G., Myszkowski, K., Seidel, H.-P.: Beyond tone mapping: enhanced depiction of tone mapped HDR images. Comput. Graph. Forum **25**(3), 427–438 (2006)
31. Tomasi, C., Manduchi, R.: Bilateral filtering for gray and color images. In: Proceedings of International Conference on Computer Vision (ICCV98), pp. 839–846, Bombay, India (1998)
32. Tsin, Y., Liu, Y., Ramesh, V.: Texture replacement in real images. In: IEEE Conference on Computer Vision and Pattern Recognition’01 (CVPR01), Hawaii, USA, pp. 539–544 (2001)
33. Xu, R., Pattanaik, S.N., Hughes, C.E.: High-dynamic range still-image encoding in JPEG 2000. IEEE Comput. Graph. Appl. **25**(6), 57–64 (2005)
34. Zelinka, S., Fang, H., Garland, M., Hart, J.C.: Interactive material replacement in photographs. In: Proceedings of Graphics Interface’05, Victoria, pp. 227–232 (2005)
35. Zhang, R., Tsai, P.S., Cryer, J.E., Shah, M.: Shape from shading: a survey. IEEE Trans. Pattern Anal. Machine Intelligence **21**(8), 690–706 (1999)

JIANBING SHEN is a PhD candidate at the State Key Lab of CAD&CG, Zhejiang University, P.R. China. He received his BSc and MSc degrees in mechatronic engineering from Zhejiang University of Technology. His research interests include texture synthesis, image completion, and high dynamic range imaging and processing.

XIAOGANG JIN is a professor at the State Key Lab of CAD&CG, Zhejiang University. He received his BSc degree in computer science in 1989, MSc and PhD degrees in applied mathematics in 1992 and 1995, all from Zhejiang University. His current research interests include implicit surface computing, special effects simulation, mesh fusion, texture synthesis, crowd animation, cloth animation and facial animation.



HANQIU SUN is an associate professor of the Department of Computer Science and Engineering, The Chinese University of Hong Kong. She received her PhD degree in computer science from the University of Alberta, Canada. Her current research interests include virtual & augmented reality, interactive graphics/animation, hypermedia, touch-enabled haptics simulation.