Edge-Preserving Image Decomposition Based on Guided Upper/Lower Envelops

Soo-Chang Pei
Department of Electrical Engineering
National Taiwan University
Taipei, Taiwan, R.O.C.
Email: pei@cc.ee.ntu.edu.tw

Chih-Tsung Shen
Institute of Information Science
Academia Sinica
Taipei, Taiwan, R.O.C.
Email: shenchihtsung@gamil.com

Wen-Hui Chu
GICE
National Taiwan University
Taipei, Taiwan, R.O.C.
Email: jujupp1116@gamil.com

Abstract— **In this paper, we present an image decomposition method based on guided upper/lower envelops of the intensity signal. First, we estimate our upper/lower envelops by using a estimator guided by the gradient (edges). Second, using the guided envelops, we easily obtain the edge-preserving base layer of the intensity signal and its corresponding detail layer. In the end, we not only propose the JND-based detail boosting for image enhancement but also demonstrate our image abstraction/stylization. Experimental results show that our proposed method is promising as compared to the existing methods.**

I. Introduction

Image decomposition refers to decompose the intensity signal into several layer signals: base layer and detail layer. With these decomposed signals, we can not only obtain more flexibility to enhance each signal but also develop plenty of applications, such as Retinex [1] [7] [8], HDR imaging [3] [5] [13], low-power backlight [9] [12], image abstraction/stylization [6] [11], and image fusion [13]. Due to the wide variety of interesting applications, image decomposition becomes a vital technique in the field of image processing, computer vision, computer graphics and computational photography.

In 1997, Jobson et al. obtained their base layer by convoluting the intensity signal with a set of gaussian filters. Since they did not constrain the behaviors of the base layer around edges, their results suffer serious Halo artifacts (intensity reversals) [1]. In 1998, Tomasi et al. proposed their bilateral filtering to obtain the edge-preserving base layer. Their bilateral filtering inspires researchers to develop the edge-aware processing while branches out thousands of applications [2]. In 2002, Durand et al. proposed their linear approximation so as to adopt Fast Fourier Transformation to replace Tomasi et al.'s spatial approach. They also demonstrated their idea for displaying the high-dynamic range image using their base layer of a single image [3]. In 2006, Meylan et al. used the adaptive filter to obtain the base layer while render their HDR image [5]. Lately, Subr et al. obtained their base layer using the local maxima/minima of the intensity signal and the edge-aware interpolation technique [14].

In this paper, we borrow the idea of Kimmel et al.'s [4] to estimate the upper envelop of the intensity signal and guide it with gradient (edges) to construct an edge-preserving upper envelop. Similarly, we obtain the edge-preserving lower envelop by taking the reverse operation and the same process of the upper envelop. Our base layer is the mean of these two envelops, and the detail layer is the difference between the intensity signal and our base layer. Since our guided upper/lower envelops are edge-preserving, the edge-preserving base layer is guaranteed. For image enhancement, we also propose a JND-base boosting for detail layer. In the end, experimental results on image enhancement and image stylization reveal our proposed method is promising.

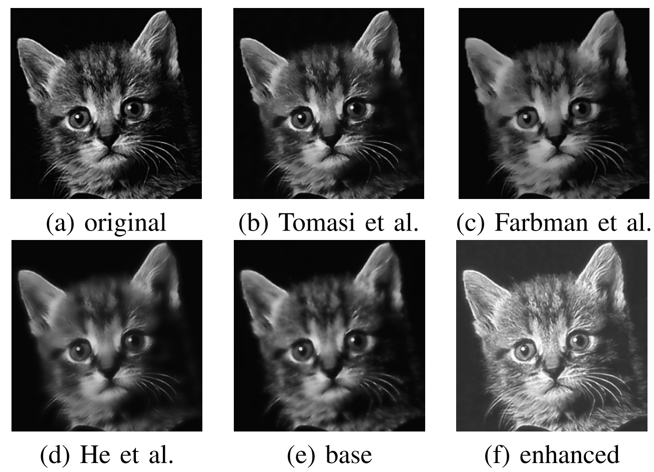


Fig. 1. Image enhancement. (a) The original image, (b) Tomasi et al.'s bilateral filtering, (c) Farbman et al.'s WLS, (d) He et al.'s guided filtering, (e) our base layer, and (f) our enhanced image.

II. OUR PROPOSED METHOD

Our proposed method contains four steps: guided upper envelop estimation, guided lower envelop estimation, base layer processing and JND-based boosting for detail layer. We introduce the whole method step by step.

A. Upper Envelop Estimator

First, in order to avoid the color-shift problem, we transfer our images from RGB color space into HSV color space and apply our image decomposition method only on V channel. That is, the V channel signal is our intensity signal $I(x, y)$. Besides, we adopt the Non-Local-Mean image denoising method [10] on each R, G, and B channel before the color transformation so as to grantee the accuracy of our image decomposition.

Second, for our guided upper envelop, we deduce a quadratic equation with the gradient guides around edges. Let $U(x, y)$ is the desired upper envelop and we reference [4] to obtain $U(x, y)$ using the quadratic cost function:

$$F(U(x,y)) = \int_{\Omega} (\|\nabla U(x,y)\|^2 + \alpha \|U(x,y) - I(x,y)\|^2) dx dy \quad (1)$$

where Ω is the support of the image, ∇ is the first-order differential operator, and $\|\cdot\|$ denotes the absolute value. We adopt the gradient-descent algorithm to minimize $F(U(x, y))$. An iteration of this gradient-descent algorithm can be formulated as follows:

$$U_j(x,y) = U_{j-1}(x,y) - \beta \cdot G_F(x,y) \quad (2)$$

where $U_j(x, y)$ and $U_{j-1}(x, y)$ are the signals of upper envelop at step j and $j - 1$, respectively, β is the line-search step size, and $G_F(x, y)$ represents the gradient of $F(U(x, y))$. Similar to Kimmel et al., we can approximate the gradient signals as follows:

$$G_F(x,y) = \frac{\partial F(U)}{\partial U} \quad (3)$$

$$= -\Delta U(x,y) + \alpha \cdot (U(x,y) - I(x,y)) \quad (4)$$

$$\approx -U(x,y) * K_{lap}(x,y) + \alpha \cdot (U(x,y) - I(x,y)) \quad (5)$$

where Δ is the second-order Laplacian differential operator, which can be approximated by a linear convolution with the spatial filter K_{lap}.

$$K_{lap} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

In the end of each iteration, we guide the upper envelop to become spatial piecewise smooth meanwhile eliminate the Halo artifacts. We guide our upper envelop to change rapidly with the intensity around strong edges. That is, when intensity changes rapidly, the upper envelop is close to intensity.

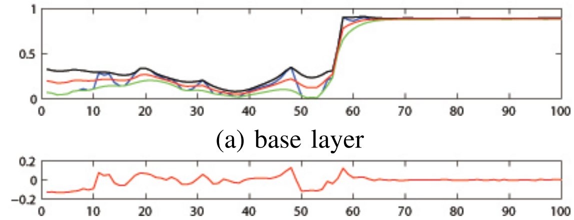
$$U_j(x,y) \leftarrow \max\{w(x,y) \cdot I(x,y) + (1 - w(x,y)) \cdot U_j(x,y), I(x,y)\} \quad (6)$$

where $w(x, y)$ is our gradient-guided weighting function associating to the gradient of intensity. The profile of our gradient-guided weighting function is described as the following expressions:

$$w(x,y) = \begin{cases} w_0, & \text{if } \nabla I(x,y) \geq TH \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

$$\nabla I(x,y) \approx \|I(x,y) * D_x(x,y)\| + \|I(x,y) * D_y(x,y)\| \quad (8)$$

where $\nabla I(x, y)$ represents the guiding gradient, TH is the threshold of $\nabla I(x, y)$, $D_x(x, y)$ and $D_y(x, y)$ are the first derivative of Gaussian (FDOG) operators respect to x-direction and y-direction, respectively. Observe that when $\nabla I(x, y)$ is smaller than TH, we have $w(\nabla I(x, y)) = 0$ meanwhile $U_j(x, y)$ is widely relaxed. After several iterations, we obtain our convergent guided upper envelop $U_\infty(x, y)$.



(a) base layer

(b) detail layer

Fig. 2. Image decomposition. (a) The blue line is the intensity. The black line represents our guided upper envelop. The green line represents our guided lower envelop. The red line is our edge-preserving base layer. (b) The red line represents our detail layer.

B. Lower Envelop Estimator

To estimate the lower envelop, we adopt the upper envelop estimator by substituting $I(x, y)$ by its reverse signal:

$$\widetilde{I}(x,y) = W - I(x,y) \quad (9)$$

where W is the white value (equal to 1 in normalized images or 255 for 8-bits images).

Similarly, we can obtain the convergent output $\widetilde{U_\infty}(x, y)$ by adopting the same procedure of the upper envelop estimator:

$$F(\widetilde{U}(x,y)) = \int_{\Omega} (\|\nabla \widetilde{U}(x,y)\|^2 + \alpha \|\widetilde{U}(x,y) - \widetilde{I}(x,y)\|^2) dx dy \quad (10)$$

Our guided lower envelop can be obtained by taking the reverse of $\widetilde{U_\infty}(x, y)$:

$$L_\infty(x,y) = W - \widetilde{U_\infty}(x,y) \quad (11)$$

Since we reuse the same guided upper envelop estimator to estimate our guided lower envelop, we can save the area of the Integrated Circuits (IC), which is one of the critical issues in IC Design.

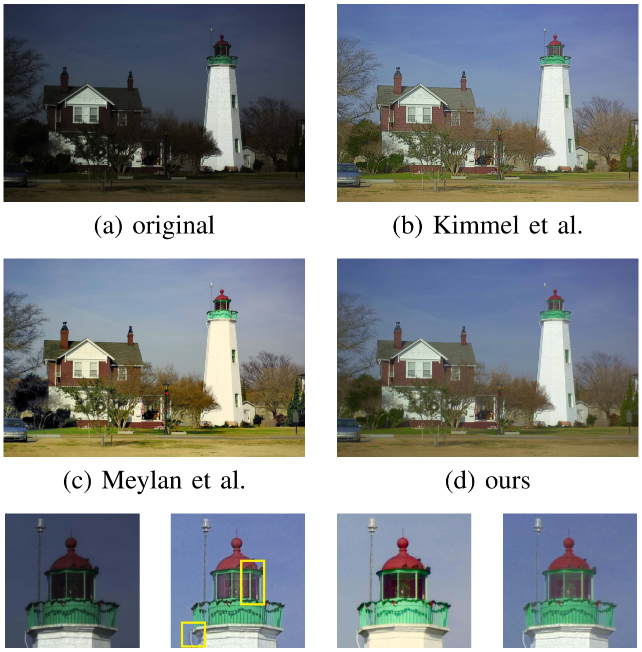
C. Base Layer Processing

Since our guided upper/lower envelops are given, we can easily obtain our base layer by taking the mean operation:

$$B(x,y) = \frac{1}{2} \cdot (U_\infty(x,y) + L_\infty(x,y)) \quad (12)$$

Because our guided upper/lower envelops are edge-preserving, our base layer is guaranteed to be edge-preserving. Moreover, we can tune up the base layer using gamma correction for image enhancement.

$$B_{EN}(x,y) = W \cdot (\frac{B(x,y)}{W})^{1/\gamma} \quad (13)$$



(a) original (b) Kimmel et al.
(c) Meylan et al. (d) ours
(e) (f) (g) (h)

Fig. 3. Image enhancement. (a) The original image, (b) Kimmel et al.'s enhanced image, (c) Meylan et al.'s HDR image, (d) our enhanced image, and (e)-(h) are the magnified regions of (a)-(d), respectively.

D. JND-Based Boosting for Detail Layer

Since the base layer $B(x, y)$ is given, we can deduce our detail layer:

$$D(x, y) = I(x, y) - B(x, y) \tag{14}$$

For image enhancement, we proposed a JND-based boosting for our detail layer. Just-noticeable-difference (JND) is the smallest stimulus for human vision to perceive the difference between the operating pixel intensity and its background (or adaptation) intensity. To calculate the JND, we modify the JND profiles proposed by Chio et al. [7] and combine their JND profile with our base layer. In this paper, we calculate the JND as follows:

$$JND(x, y) = \mu + \sigma \cdot (B(x, y) * M(x, y)) \tag{15}$$

where "$*$" denotes the 2D convolution operation, μ and σ are constants, and $M(x, y)$ denotes the background average mask as follows:

$$M = \frac{1}{32}\begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 2 & 2 & 1 \\ 1 & 2 & 0 & 2 & 1 \\ 1 & 2 & 2 & 2 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{pmatrix}$$

If the absolute value of our $D(x, y)$ is larger than $JND(x, y)$, the operating pixel (x, y) is an significant pixel in human perception. As a result, we enhance this pixel by a stronger JND-related mapping. Otherwise, if $|D(x, y)|$ is not larger than $JND(x, y)$, we enhance this pixel by a weaker JND-related mapping for avoiding the un-natural artifacts as compared to the original image:

(a) original (b) Jobson et al.
(c) Meylan et al. (d) ours

Fig. 4. Image enhancement. (a) The original image, (b) Jobson et al.'s enhanced image, (c) Meylan et al.'s HDR image, and (d) our enhanced image.

$$D_{EN}(x, y) = D(x, y) \cdot \left(\frac{W + JND(x, y)}{W}\right)^{\tau(x, y)} \tag{16}$$

where $\tau(x, y)$ is an adaptive function or an uniform constant.

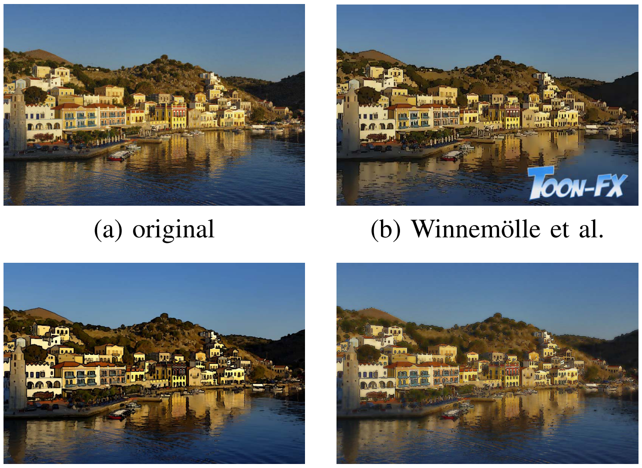
Finally, our enhanced image is obtained by merging the enhanced base layer and enhanced detail layer.

$$I_{EN}(x, y) = B_{EN}(x, y) + D_{EN}(x, y) \tag{17}$$

III. EXPERIMENTAL RESULTS

For image denoising, we set the ratio of search window equals 5, the ratio of similarity window equals 2, and the degree of filtering equals 5. For quadratic equation of our upper envelop estimator, we set $\alpha = 0.05$, $\beta = 0.2$, $w0 = 0.5$, $TH = 0.75$(for normalized image), and the iteration number is set to 30. For image enhancement, we set $\gamma = 2.2$ for the gamma correction of our base layer and set $\mu = 0.156$(for normalized image) and $\sigma = 0.12301$ for our JND-based detail boosting. Besides, we uniformly set $\tau(x, y) = 2.2$ for $|D(x, y)| > JND(x, y)$; otherwise, we set $\tau(x, y) = 0$. For image abstraction/stylization, we adopt our un-corrected base layer and our stylized edges.

Fig. 1(a) shows the first input image. Fig. 1(b) is the resulting base layer of Tomasi et al.'s bilateral filtering. Fig. 1(c) is the base layer of Farbman et al.'s weighted least squares optimization. Fig. 1(d) is the base layer of He et al.'s guided filtering [15]. Fig. 1(e) is the base layer of our method, and Fig. 1(f) is our enhanced image. Tomasi et al.'s bilateral filtering may keep too much detail signal of texture regions when the surrounding parameter is chosen to small. Besides, Farbman et al.'s base layer and He et al.'s base layer are hard to distinguish the boundaries between hair and the background. Our base layer is free from their drawbacks, and our enhanced image demonstrates the potential of our JND-based detail boosting.



(a) original (b) Winnemölle et al.

(c) Farbman et al. (d) ours

Fig. 5. Image abstraction/stylization. (a) The original image, (b) Winnemöller et al.'s stylized image, (c) Farbman et al.'s stylized image, and (d) our stylized image.

Fig. 2(a) is our image decomposition. The blue line is the intensity. The black line represents our guided upper envelop. The green line represents our guided lower envelop. The red line is our edge-preserving base layer. As we can see that our guided upper/lower envelops are close to the original intensity when the edge is sharp. Since our base layer is the mean of our upper/lower envelops, we can easily get the edge-preserving base layer. Fig. 2(b) shows our corresponding detail layer.

The second input image (Fig.3(a)) and the third input image (Fig.4(a)), of size 2000×1312, are both downloaded from the TruView Imaging Company. Fig. 3(a) shows the second input image. Fig. 3(b) is Kimmel et al.'s enhanced image. Fig. 3(c) is Meylan et al.'s enhanced image. Fig. 3(d) is our enhanced image. Fig. 3(e)-(h) are the magnified regions of Fig. 3(a)-(d), respectively. As we can see that Fig. 3(b,f) suffer the Halo artifacts while Fig. 3(c,g) suffer the color-shifting problem (shifting to green). Our enhanced image is free from these two drawbacks. Similarly, Fig. 4(a) shows the third input image. Fig. 4(b) is Jobson et al.'s enhanced image. Fig. 4(c) is Meylan et al.'s enhanced image. Fig. 4(d) is our enhanced image. As we can see that Jobson et al. fail to correct the regions around pillars. Besides, due to the PCA transformation on color, Meylan et al.'s enhanced image suffers the color-shifting. Our enhanced image is corrected around the pillars while free from color-shifting problem.

Fig. 5 and Fig. 6 show the comparisons between our image abstraction/stylization method and the existing methods. Fig. 5(a) show the four input image. Fig. 5(b) is Winnemöller et al.'s stylized image. Fig. 5(c) is Farbman et al.'s fine-scale stylized image. Fig. 5(d) is our stylized image. We adopt our base layer and pick up the thin edges to express another stylization as compared to Winnemöller et al.'s and Farbman et al.'s. Similarly, Fig. 6(a) shows the fifth input image, and Fig. 6(b) is our stylized image. It is easily observed that we smooth the original image while preserving the edges successfully.

(a) original (b) ours

Fig. 6. Image abstraction/stylization. (a) The original image, and (b) our stylized image.

IV. Conclusion

To conclude, we propose an edge-preserving image decomposition method based on guided upper/lower envelops. First, we obtain our edge-preserving upper/lower envelop using an estimator guided by the gradient of intensity. Second, we obtain our edge-preserving base layer by taking the mean of these upper/lower envelops. Besides, we propose our JND-based detail boosting for image enhancement while we also demonstrate our image abstrastion/stylization results. Experimental results show that our method is promising.

References

[1] D. J. Jobson, Z. Rahman and G. A. Woodell, *A multiscale retinex for bridging the gap between color images and the human observation of scenes,* IEEE Trans. on Image Processing, Vol. 6(7), pp.965-976, 1997.

[2] C. Tomasi and R. Manduchi, *Bilateral filtering for gray and color images,* ICCV, pp.836-846, 1998.

[3] F. Durand and J. Dorsey, *Fast bilateral filtering for the display of high-dynamic range images,* ACM Trans. on Graphics, Vol. 21(3), pp. 257V266, 2002.

[4] R. Kimmel, M. Elad, D. Keshet and I. Sobel, *A variational framework for retinex,* Int. J. Computer Vision, Vol. 52(1), pp.7-23, 2003.

[5] M. Meylan and S. Süsstrunk, *High dynamic range image rendering with a retinex-based adaptive filter,* IEEE Trans. on Image Processing, Vol. 15(9), pp.2820-2830, 2006.

[6] H. Winnemöller, S. C. Olsen and B. Gooch, *Real-time video abstraction,* ACM Trans. on Graphics, Vol. 25(3), pp.1221-1226, 2006.

[7] D. H. Choi, I. H. Jang, M. H. Kim and N. C. Kim, *Color image enhancement based on single-scale retinex with a JND-based nonlinear filter,* ISCAS, pp.3948-3951, 2007.

[8] S. Saponara, L. Fanucci, S.Marsi, G. Ramponi, D. Kammler and E. M. Witte,*Application-specific instruction-set processor for retinex-like image and video processing,* IEEE Trans. on Circuits and Systems - II: Express Briefs, Vol. 54(7), pp.596-600, 2007.

[9] T.-H. Huang, C.-K. Liang, S.-L. Yeh and H. H. Chen, *JND-based enhancedment of perceptibility for dim images,* ICIP, pp. 1752-1755, 2008.

[10] A. Buades, B. Coll, and J. M. Morel, *Nonlocal image and movie denoising,* Int. J. Computer Vision, Vol. 76, pp.123-139, 2008.

[11] Z. Farbman, R. Fattal, D. Lischinski and R. Szeliski, *Edge-preserving decompositions for multi-scale tone and detail manipulation* ACM Trans. on Graphics, Vol. 27, pp.671-680, 2008.

[12] P.-S. Tsai, C.-K. Liang, T.-H. Huang and H. H. Chen,*Image Enhancement for Backlight-Scaled TFT-LCD Displays,* IEEE Trans. on Circuits Systems for Video Technology Vol.19(4), pp. 574-583, 2009.

[13] S. Paris, and F. Durand, *A fast approximation of the bilateral filter using a signal processing approach,* Int. J. Computer Vision, Vol. 81(1), pp. 24-52, 2009.

[14] K. Subr, C. Soler and F. Durand, *Edge-preserving multiscale image decomposition based on local extrema,* ACM Trans. on Graphics, vol. 28(5), 2009.

[15] K. He, J. Sun and X. Tang, *Guided image filtering,* ECCV, pp.1-14, 2010.