Denoising and Effective Contrast Enhancement for Dynamic Range Mapping

G. Kiruthiga
Department of Electronics and Communication
Adithya Institute of Technology
Coimbatore

B. Hakkem
Department of Electronics and Communication
Adithya Institute of Technology.
Coimbatore

ABSTRACT
This paper introduces a new tone mapping algorithm that performs denoising and contrast enhancement for dynamic range mapping. The proposed local TM algorithm compresses the luminance of high dynamic range (HDR) image using luminance compression function and decomposes the compressed luminance of HDR image into multi-scale subbands using the discrete wavelet transform. The decomposed low frequency subband is filtered using a bilateral filter and high frequency subbands are smoothed using soft-thresholding for noise reduction. The filtering is followed by enhancement. The local contrast is enhanced in the dynamic ranges of the filtered subbands. Then the color of the tone mapped image is reproduced using an adaptive saturation control parameter. Finally, the edges are reconstructed in the tone mapped image. Thus the tone-mapped image is generated using the proposed local TM. The effectiveness of the proposed local TM algorithm is realised in simulation results. This stands good for visual quality and local contrast which can be used in various displays with noise reduction and contrast enhancement.

Index Terms
bilateral filter, soft-Thresholding, contrast enhancement, high dynamic range, noise reduction, tone mapping.

1. INTRODUCTION
Real world scenes have various intensity ranges which expand from dim starlight to direct sunlight. However, existing cameras can only capture a limited range of intensities. While digital imaging technology now enables us to capture full dynamic range of the real world scene, still we are limited by the low dynamic range displays. Thus the scene can be visualized on a display monitor only after the captured high dynamic range is compressed to available range of the display device. This has been referred to as the tonemapping problem. Tone mapping (TM) is a method that maps high dynamic range (HDR) image to low dynamic range (LDR) image for display devices with limited dynamic range (DR). Tonemapping is also called as dynamic range mapping. HDR image with a dynamic range of 100,000:1 will be converted into an image with dynamic range of 255:1.

HDR image, called radiance map, is generated by combining LDR images, which are captured with varying exposure setting using auto exposure bracketing in a digital camera [1]. Sometimes HDR image is captured using an HDR camera, which has high and low sensitivity sensors per pixel to increase dynamic range. Noise is contained in HDR images, which are captured under the low light condition such as dim interior and night scene [8]. Also the dark region of HDR image has a low signal to noise ratio (SNR). Most conventional TM algorithms do not consider noise. HDR image contains both coarse-grain (low-frequency) and fine-grain (high-frequency) noise. Fine-grain noise is easy to reduce, whereas coarse-grain noise is relatively hard to smooth because it is difficult to distinguish between signal and noise. The larger number of LDR images we use, the more the noise in HDR image is reduced. However, the number of LDR images used in HDR image generation is limited in consumer products due to the processing time.

In this paper, noise reduction method and an adaptive contrast enhancement for local TM were proposed. After initial compression of the luminance of HDR image, the proposed local TM algorithm decomposes an initial compressed luminance into multi-scale subbands using the discrete wavelet transform. The decomposed subbands are filtered using a bilateral filter (*LL* subband) and soft-Thresholding (*LH*, *HL*, and *HH* subbands). And then, the local contrast is enhanced by an adaptive weight, which is derived from the luminance compression function with the color constraint [3]. Finally, the color of the tone-mapped image is reproduced using an adaptive saturation control parameter [2]. In experiments, the tone-mapped color image of the proposed local TM algorithm is compared with those of the conventional TM algorithms with post-processing (i.e., noise reduction using the standard bilateral filter). Computer simulation with noisy HDR images shows the effectiveness of the proposed local TM algorithm in terms of the visual quality as well as the local contrast and detail preservation.

The rest of the paper is organized as follows. Section II describes the conventional TM algorithms. Section III proposes a TM algorithm, which consists of image decomposition, denoising using a bilateral filter and soft-thresholding, luminance compression by considering local contrast, and color reproduction. Experimental results with HDR images are presented and discussed in Section IV, showing the effectiveness of the proposed local TM algorithm. Finally, Section V concludes the paper.

2. PREVIOUS WORK
Recently TM algorithms have been developed for reproducing the tone-mapped color image, in which color, contrast, and detail components are enhanced using luminance compression and color reproduction by considering the human visual system or the local statistical characteristic. Various TM algorithms are classified into global [11], [15] and local [1]-[4], [6], [9], [10], [12], [13] methods. Global TM algorithms are simple and fast because of using the same mapping curve for every pixel, independently of the neighboring pixels in the radiance map. These are non-linear functions with global parameters, however not performing satisfactory enhancement. The detail components are reduced and the artifacts such as false contours and false color are generated.

The simple and typical global TM algorithms include logarithmic transformation, gamma correction, histogram equalization, and linear mapping. Reinhard *et al*.'s algorithm is a relatively simple and fast TM algorithm [11]. The local TM algorithms apply different mapping curves to different regions or compositions of an image. Most local TM algorithms decompose an image into different scales or compositions. Some of the local TM algorithms are Li et al.'s algorithm, iCAM algorithm and Shan et al.'s algorithm. Li *et al*.'s algorithm uses a symmetrical analysis-synthesis filer bank, and applies local gain control to the subband [10]. iCAM algorithm is a new image appearance model, which incorporates the spatial processing models in the human visual system for contrast enhancement, photoreceptor light adaptation function that enhances local details, and functions that predict a wide range of color appearance phenomena [9]. Shan *et al*.'s algorithm performs local linear adjustments on small overlapping windows over the entire HDR image [4]. These methods are not enough to enhance the contrast, to represent the color and to reduce halos. Also previous works generate false contours in the highlight region.

3. PROPOSED ALGORITHM

The proposed local TM algorithm constructs the tone-mapped color image with high contrast from the noisy HDR image. To generate the HDR image, a set of five LDR images with different exposures and high ISO setting is used. Fig. 1 shows the block diagram of the proposed local TM algorithm. The input, HDR image, c_i is generated using five LDR images in high ISO setting. The proposed local TM algorithm consists of initial luminance compression, image decomposition and synthesis, noise reduction, local contrast enhancement, color reproduction and edge reconstruction. Each block is described in the following.

3.1 Subband Decomposition

In the proposed local TM algorithm, the luminance of the HDR image is compressed using a simple luminance compression function, a logarithmic function. And then, we decompose the initial compressed luminance using the discrete Haar wavelet transform, which is applied separately in the *x* and *y* directions and is iterated upto level *K*. The Haar wavelet consists of a low-pass filter [1 1] and a high-pass filter [1 –1], which are the simplest filters to implement. The filter outputs are subsampled by a factor of two in each direction. (If the input has *N* samples, with *N* assumed to be even, each subband has *N*/2 subband coefficients.) The initial compressed luminance is split into a set of low-frequency and high-frequency subbands at $\mathbf{x} = (x, y)$: $b^{LL}(\mathbf{x})$, $b^{LH}(\mathbf{x})$, $b^{HL}(\mathbf{x})$, and $b^{HH}(\mathbf{x})$. In a standard separable *K*-level subband pyramid, there are $3K+1$ subbands.

The sub-sampled pyramids are highly efficient in view of computation, representation, and reduction of coarse-grain noise, because the number of samples in subbands is reduced at each level. Coarse-grain noise becomes fine-grain noise as the compressed luminance is decomposed into multi-scale subbands. In the proposed local TM algorithm, the denoised subbands are convolved with the synthesis filters and summed to reconstruct the adaptive compressed luminance *lo*.

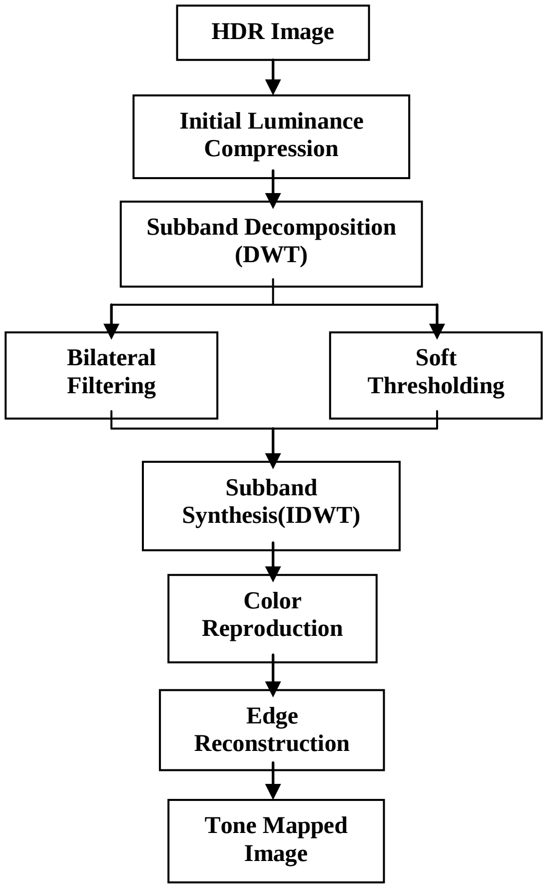


Fig 1: Block diagram of the proposed local TM algorithm

3.2 Denoising using a bilateral filter and Soft-Thresholding

In the proposed local TM algorithm, the decomposed subbands are filtered using a denoising filter, which consists of bilateral filtering and soft-thresholding. The *LL* subband (low-frequency subband) is filtered using the bilateral filter, whereas *LH*, *HL*, and *HH* subbands (high-frequencysubbands) are smoothed using soft-thresholding for effective noise reduction.

The bilateral filter is a nonlinear filter that does spatial averaging without smoothing edges. It has shown to be an effective image denoising technique. It can also be applied to the blocking artifacts reduction. Bilateral filtered *LL* subband is defined as

$$\hat{b}_K^{LL}(\mathbf{x}) = \frac{1}{s(\mathbf{x})}\sum_{\mathbf{x}'\in\Omega} G_{\sigma_s}(\mathbf{x}-\mathbf{x}')\, G_{\sigma_r}\left(b_K^{LL}(\mathbf{x}) - b_K^{LL}(\mathbf{x}')\right) b_K^{LL}(\mathbf{x}')$$

$$s(\mathbf{x}) = \sum_{\mathbf{x}'\in\Omega} G_{\sigma_s}(\mathbf{x}-\mathbf{x}')\, G_{\sigma_r}\left(b_K^{LL}(\mathbf{x}) - b_K^{LL}(\mathbf{x}')\right)$$

where $b_k^{LL}(x)$ denotes the *LL* subband of the compressed luminance, *G* represents a Gaussian function, and Ω signifies the set of neighboring pixels whose center pixel is at **x**. The bilateral filter takes a weighted sum of the pixels in a local neighborhood; the weights depend on both the spatial distance and the intensity distance. [16]. The subscripts σ_s and σ_r denote standard deviations of Gaussian weight functions in the spatial domain and intensity domain respectively. $s(\mathbf{x})$ denotes the normalization term.

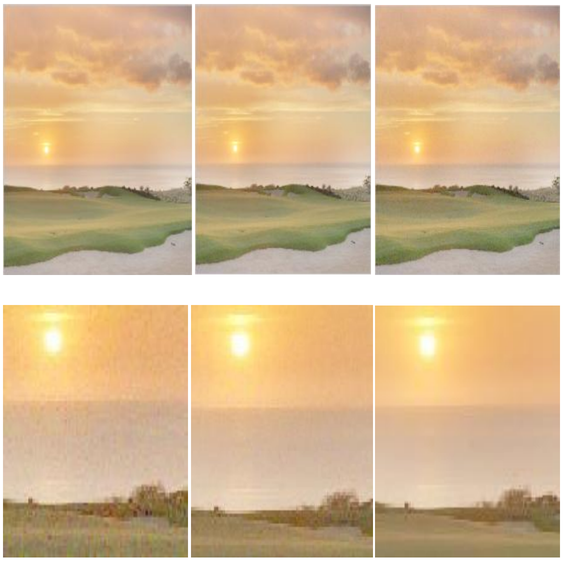
The soft-thresholding function is used to smooth high-frequency subbands, which is expressed as

$$\hat{b}_k^j(\mathbf{x}) = \begin{cases} \text{sign}\left(b_k^j(\mathbf{x})\right)\left(\left|b_k^j(\mathbf{x})\right| - \lambda_k\right), & \left|b_k^j(\mathbf{x})\right| > \lambda_k \\ 0, & \text{otherwise} \end{cases}$$

where $b_k^j(x)$ represents high-frequency subbands (*j*=*LH*, *HL*, and *HH* subbands at level *k*) at **x** = (*x*, *y*). λ_k denotes the threshold at level *k*.

A Haar wavelet coefficient is compared to a threshold value and is set to zero if its magnitude is less than the threshold. Otherwise, the wavelet coefficient is kept. The threshold can distinguish between the significant coefficients (signal) and the insignificant coefficients (noise).

In this paper, we use BayesShrink method [7], [14] for soft-thresholding. Fig. 2 shows the performance comparison of soft-thresholding with different threshold value λ. Figs. 2(a), 2(b), and 2(c) illustrate the denoised tone-mapped images and their enlarged images of noisy HDR image with λ=0.01, 0.0353 (adaptive threshold computed by BayesShrink method [14]), and 0.05, respectively.



(a) (b) (c)

Fig 2: Performance comparison of soft-thresholding with different λ values. (a) λ=0.01, (b) λ =0.0353, (c) λ=0.05

In Fig. 2(a), coarse-grain noise remains and the signal is preserved well, as the threshold value (λ =0.01) smaller than the adaptive threshold is used. On the contrary, in Fig. 2(c) coarse-grain noise is reduced well whereas the edge is degraded, as the threshold value (λ =0.05) larger than the adaptive threshold is used.

3.3 Luminance compression by considering Local contrast

In the proposed local TM algorithm, the adaptive compressed luminance l_o is generated by

$$l_o(\mathbf{x}) = w(\mathbf{x}) \cdot \hat{b}_K^{LL}(\mathbf{x}) + \sum_{k=1}^{K} \hat{b}_k^j(\mathbf{x})$$

where $\hat{b}_k^j(\mathbf{x})$ denotes the denoised high-frequency subbands. $w(\mathbf{x})$ represents the adaptive weight at **x**, which is defined as [1], [3]

$$w(\mathbf{x}) = \alpha \cdot \left(\frac{\hat{b}_K^{LL}(\mathbf{x})}{\bar{b}_K^{LL}(\mathbf{x})} \right)^{p'(\mathbf{x})}$$

with α representing the scale constant, expressed as

$$\alpha = \frac{1}{\min\left\{p\left(\bar{b}_K^{LL}\right), 2\right\}}$$

for limiting the scale of the adaptive weight *w*. $\bar{b}_K^{LL}(\mathbf{x})$ denotes the local mean of $\hat{b}_K^{LL}(\mathbf{x})$ in the 3×3 mask and $p(\cdot)$ is derived from the luminance compression function [3]. $p'(\mathbf{x})$ represents the exponent of an adaptive weight and is expressed as

$$p'(\mathbf{x}) = \beta \cdot p\left(\bar{b}_K^{LL}(\mathbf{x})\right)$$

where β is a local contrast enhancement parameter (local contrast enhancer) which controls the amount of local contrast enhancement.

3.4 Color Reproduction

In order to assign the color of the tone-mapped image, we use an adaptive color saturation control parameter [1], [2]. In the over-exposed region such as reflected area, bright sky, streetlights, and outside of the window in a sunny day, the color saturation control parameter *s* is set to a small value to reproduce natural color. In the under-exposed region such as shaded area and inside of the building, the color and details are rendered well in the tone-mapped image with a large color saturation control parameter *s*. The color saturation control parameter *s* is limited to a fixed maximum value s_{max}.
That is, automatic color saturation control parameter *s* at **x** is determined by

$$s(\mathbf{x}) = \min\left\{ s_{\max}, \frac{a}{l_o(\mathbf{x})} \right\}$$

where *a* is a scale constant, $0 \le a \le 1$. s_{max} can be tuned to produce the tone-mapped color images with different saturation. The larger maximum value s_{max} makes the tone mapped image visually more colorful. The default value of s_{max}=1.0 produces visually satisfactory tone-mapped images for most HDR image sets used in experiments. In the proposed local TM algorithm, the tone-mapped color image c_o at **x** is generated by

$$c_o(\mathbf{x}) = \left(\frac{c_i(\mathbf{x})}{l_i(\mathbf{x})} \right)^{s(\mathbf{x})} \left\{ w(\mathbf{x}) \cdot \hat{b}_K^{LL}(\mathbf{x}) + \sum_{k=1}^{K} \hat{b}_k^j(\mathbf{x}) \right\}$$

$$= \left(\frac{c_i(\mathbf{x})}{l_i(\mathbf{x})} \right)^{s(\mathbf{x})} l_o(\mathbf{x})$$

where c_o represents one of color channels (red, green, or blue) of the tone-mapped color image. The enhanced color channels are reproduced by adaptively compressed luminance l_o and an adaptive color saturation control parameter *s*.

3.5 Edge Reconstruction

The bilateral filter performs edge preserved smoothing in low frequency subbands but the edges are smoothed in high frequency subbands. So to preserve the edges in the output image, edge reconstruction is done at the final step.

For edge reconstruction first the edges in the HDR image is detected and then at the final step this image is fused with the color reproduced image by taking mean for every pixels in the images.
There are many methods of detecting edges; the majority of different methods may be grouped into these two categories:
1) *Gradient:* The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. For example Roberts, Prewitt, Sobel where detected features have very sharp edges.

2) *Laplacian:* The Laplacian method searches for zero crossings in the second derivative of the image to find edges e.g. Marr-Hildreth, Laplacian of Gaussian etc. An edge has one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location.

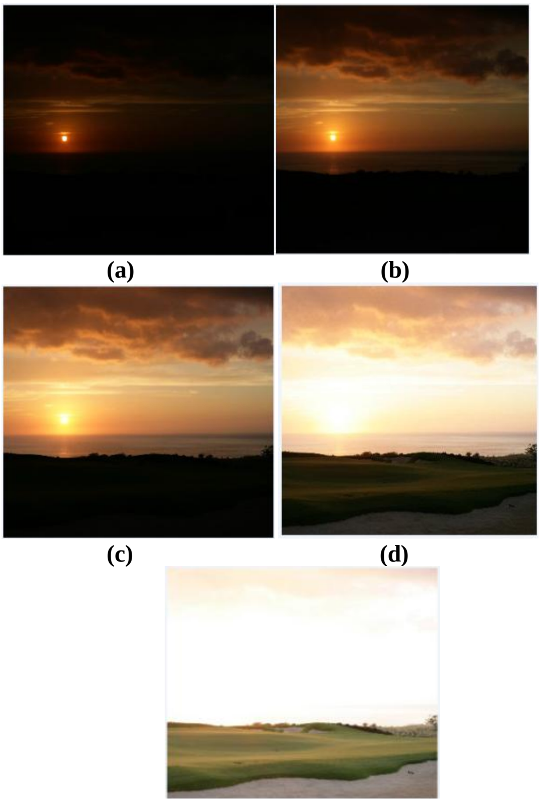
The Sobel operator is an example of the gradient method. The Sobel operator is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. The Sobel operator performs a *2-D* spatial gradient measurement on images. Transferring a *2-D* pixel array into statistically uncorrelated data set enhances the removal of redundant data, as a result, reduction of the amount of data is required to represent a digital image. The Sobel edge detector uses a pair of *3 x 3* convolution masks, one estimating gradient in the x-direction and the other estimating gradient in *y*–direction. Edges consist of meaningful features and contained significant information. Applying an edge detector to an image may significantly reduce the amount of data to be processed and may therefore filter out information that may be regarded as less relevant, while preserving the important structural properties of an image.

In this paper sobel method is used to find the edges in the HDR image. The image obtained by sobel method is then fused with the color reproduced image to get the tone mapped image. Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The test HDR image is generated by combining five LDR images of the same scene but with different exposures (-2, -1, 0, +1 and +2 EV).

The five LDR images used to create the HDR image is shown in Fig. 3. In conventional TM algorithms, coarse-grain noise remains in the output image. Fig. 4 shows the tone-mapped image by the proposed local TM algorithm, where coarse-grain noise in smooth and dark regions is greatly reduced and local contrast component is enhanced well.



(a) **(b)** **(c)** **(d)** **(e)**

Fig 3: LDR images with different exposure values. (a) -2EV, (b) -1EV, (c) 0EV, (d) +1EV, (e) +2EV

Fig 4: Tone Mapped Image of Proposed Algorithm

For the proposed local TM algorithm, the Haar wavelet filter is used for decomposition (K=2). In our experiments, we use BayesShrink method [14] for selecting the threshold value λ_k.

5. CONCLUSION

This paper proposes a high dynamic range compression method with noise reduction method and an adaptive contrast enhancement. This algorithm effectively suppresses the global contrast while preserving local image structure details. The proposed local TM algorithm consists of initial luminance compression, image decomposition, noise reduction, local contrast enhancement, image synthesis, color reproduction and edge reconstruction. Noise reduction and color reproduction methods can be combined with other TM algorithms for noise and false color suppression. The tone-mapped image of the proposed local TM algorithm gives better image quality than those of the conventional TM algorithms. It also improves the local contrast and suppresses artifacts such as halo artifact, false color, and false contour. That is, the proposed local TM algorithm effectively reduces coarse-grain noise and enhances the local contrast.

6. REFERENCES

[1] J. W. Lee, R.-H. Park, and S. Chang, "Local tone mapping using luminance compression and adaptive color saturation control parameter," in *Proc. 2011 IEEE Symposium Consumer Electronics ISCE 2011*, Paper No. 277, Singapore, June 2011.

[2] J. W. Lee, R.-H. Park, and S. Chang, "Local tone mapping using *K*-means algorithm and automatic gamma setting," *IEEE Trans. Consumer Electronics*, vol. 57, no. 1, pp. 209-217, Feb. 2011.

[3] J. W. Lee, R.-H. Park, and S. Chang, "Tone mapping using color correction function and image decomposition in high dynamic range imaging," *IEEE Trans. Consumer Electronics*, vol. 56, no. 3, pp. 2772–2780, Nov. 2010.

[4] Q. Shan, J. Jia, and M. S. Brown, "Globally optimized linear windowed tone mapping," *IEEE Trans. Visualization and Computer Graphics*, vol. 16, no. 4, pp. 663–675, July/Aug. 2010.

[5] T.-H. Min, R.-H. Park, and S. Chang, "Histogram based ghost removal in high dynamic range images," in *Proc. IEEE Int. Conf. Multimedia and Expo 2009*, pp. 530–533, New York, June/July 2009.

[6] R. Mantiuk, R. Mantiuk, A. Tomaszewska, and W. Heidrich, "Color correction for tone mapping," *Eurographics 2009*, vol. 28, no. 2, pp. 193–202, Mar./Apr. 2009.

[7] M. Zhang and B. K. Gunturk, "Multiresolution bilateral filtering for image denoising," *IEEE Trans. Image Processing*, vol. 17, no. 12, pp. 2324–2333, Dec. 2008.

[8] C. Liu, R. Szeliski, S. B. Kang, C. L. Zitnick, and W. T. Freeman, "Automatic estimation and removal of noise from a single image," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 30, no. 2, pp. 299–314, Feb. 2008.

[9] J. Kuang, G. M. Johnson, and M. D. Fairchild, "iCAM06: A refined image appearance model for HDR image rendering," *J. Vis. Commun. Image Representaion*, vol. 18, no. 5, pp. 406–414, Oct.2007.

[10] Y. Li, L. Sharan, and E. H. Adelson, Compressing and companding high dynamic range images with subband architectures," *ACM Trans. Graphics*, vol. 24, no. 3, pp. 836–844, July 2005.

[11] E. Reinhard, M. Stark, P. Shirley, and J. Ferwerda, "Photographic tone reproduction for digital images," *ACM Trans. Graphics*, vol.21, no. 3, pp. 267−276, July 2002.

[12] F. Durand and J. Dorsey, "Fast bilateral filtering for the display of HDR images," *ACM Trans. Graphics*, vol. 21, no. 3, pp. 257−266, July 2002.

[13] R. Fattal, D. Lischinski, and M. Werman, "Gradient domain high dynamic range compression," *ACM Trans. Graphics*, vol. 21, no.3, pp. 249–256, July 2002.

[14] S. G. Chang, B. Yu, and M. Vetterli, "Adaptive wavelet thresholding for image denoising and compression," *IEEE Trans. Image Process.*, vol. 9, no. 9, pp. 1532–1546, Sep. 2000.

[15] J. Tumblin and G. Turk, "Low curvature image simplifiers (LCIS): A boundary hierarchy for detail-preserving contrast reduction," in *Proc. ACM SIGGRAPH2000*, pp. 83–90, New Orleans, LA, July 2000.

[16] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Proc. IEEE Int. Conf. Computer Vision*, pp. 839–846, Bombay, India, Jan. 1998.

[17] P. E. Debevec and J. Malik, "Recovering high dynamic range radiance maps from photographs," in *Proc. ACM SIGGRAPH97*, pp. 369–378, New York, Aug. 1997.

[18] Ji Won Lee, Rae-Hong Park and SoonKeun Chang, "Noise Reduction and Adaptive Contrast Enhancement for Local Tone Mapping," IEEE Transactions on Consumer Electronics, Vol. 58, No. 2, May 2012.