Single Image-Based Ghost-Free High Dynamic Range Imaging Using Local Histogram Stretching and Spatially-Adaptive Denoising

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**Abstract — ***In this paper, we present a novel high dynamic range (HDR) imaging method using a single image. The existing multiple image-based HDR methods work only on condition that there is no camera and object movement when acquiring multiple, differently exposed low dynamic range (LDR) images. To overcome such an unrealistic restriction, we make three LDR images from a single input image using local histogram stretching. An edge-preserving spatially adaptive denoising method is also proposed to suppress the noise that is amplified in the histogram stretching process. Because the proposed method self-generates three histogram-stretched LDR images from a single input image, ghost artifacts that are the result of the relative motion between the camera and objects during exposure time, are inherently removed. Therefore, the proposed method can be applied to mobile imaging devices such as a mobile phone camera and a consumer compact camera to provide the ghost artifacts free HDR function in the form of either embedded or post-processing software*[1].

Index Terms — High dynamic range imaging, HDR, Histogram stretching, Denoising.

I. INTRODUCTION

Acquisition of realistic photographs becomes easier for non-experts since high-quality imaging devices are popular in consumer electronics market. Three fundamental factors for realistic acquisition include; i) high spatial resolution, ii) accurate color reproduction, and iii) high dynamic range (HDR). HDR imaging technique has recently emerged in recent years and played an important role in bringing a new revolution to digital imaging [1].

While human vision can recognize a wide range of brightness levels over 100,000, digital imaging devices have a limited dynamic range because of the finite number of bits for pixel intensity values. To overcome the limited dynamic range, the most popular HDR imaging technique acquires multiple, differently exposed input images and appropriately fuses them to obtain the extended dynamic range and color gamut [2][3]. Whereas the multiple image-based technique can successfully provide HDR images in the static scene, it produces ghost artifacts if an object moves during the exposure time. Moreover, it is even more difficult to acquire motion-free multiple frames using a compact mobile camera with limited computational power. For this reason, a single-frame HDR algorithm is needed for consumer mobile imaging devices. On the other hand, Land has proposed the Retinex image processing method, which recovers color by estimating light source and reflectivity [4]. However, color distortion and noise are amplified during the recovery process.

In order to remove ghost artifacts in HDR image, several approaches have been proposed in the literature. Kao has proposed global and local motion stabilization to fuse a pair of registered images that are taken with different exposure [5], Choi has proposed a multi-exposure camera system which captures three consecutive frames from the same scene with different exposure times [6]. This system acquires HDR images by combining the object-shape information from the under-exposed image and the color information from the two over-exposed images possibly with motion blur. Wu has proposed a method for automatically generating HDR images in consideration of camera moment and dynamic scenes [7]. This method uses the camera response function such that the original image is presented to correct the LDR images. To mitigate the errors between the camera response function and image alignment, the corrected images are processed using image inpainting. Im has proposed LDR image registration in [8], where the camera motion is compensated to align multiple LDR images. For accurate alignment a modified elastic registration method is used. Since above mentioned methods generate an HDR image from multiple LDR images, they cannot be applied to handheld mobile imaging devices. More specifically, image registration and fusion steps in the multiple image-based HDR algorithm require high computational complexity and long processing time, which makes consumer applications impossible. Although Bilcu has proposed an

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HDR method for mobile imaging applications [9], this method does not consider camera motion during the exposure time and therefore produces ghost artifacts.

The proposed method self-generates three LDR images, such as over-exposed, normal-exposed, and under-exposed images, from a single input image using local histogram stretching. Local histogram stretching uses the weighted histogram separation (WHS) method originally proposed by Pei to specify stretching region [10]. Because the proposed HDR method uses only one image, it is inherently free from ghost artifacts. We also present an edge-preserving spatially adaptive noise removing algorithm [11] to suppress noise amplified in the process of histogram stretching. The proposed algorithm is summarized in Fig. 1.

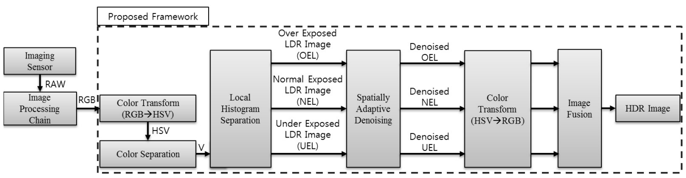


Fig. 1. The proposed ghost-free HDR algorithm using single input image.

The rest of the paper is organized as follow. We present the local histogram stretching, edge-preserving spatially adaptive denoising, and LDR images fusion method in sections 2. In section 3 we present some experimental results and compare them to existing state-of-the-art methods in [3], [8], and [9]. In section 4 we concludes the paper.

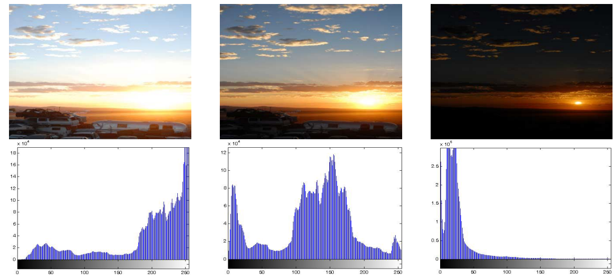
II. Single-Frame Ghost-Free HDR

In this section, we present the proposed HDR technique that consists of local histogram stretching, edge-preserving spatially adaptive noise removal, and LDR image fusion. As shown in the dotted box in Fig. 1, the proposed method generates three LDR images, an over-exposed, a normally-exposed, and an under-exposed images using local histogram stretching. We then suppress the noise that is amplified in the process of histogram stretching by using an edge-preserving spatially adaptive noise removing algorithm.

A. Local Histogram Stretching

Current HDR techniques use multiple LDR images, that are acquired using different exposure times. The histograms of three LDR images are shown in Fig. 2.

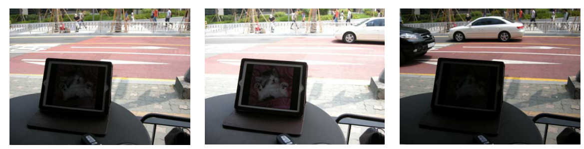
Because each LDR image is captured with different exposures, the corresponding histograms are biased towards a particular luminance range, which means that the dynamic range is limited to the corresponding brightness level. If we appropriately fuse them, we can generate an HDR image that has a histogram that is uniformly distributed over the entire brightness range. However, this approach is successful in generating an HDR images of acceptable quality only in case of a static scene as shown in Fig. 2. Most images acquired by a consumer imaging device are, however, captured under various dynamic environments.



(a) (b) (c)

Fig. 2. Three LDR images and the corresponding histogram; (a) over-exposed, (b) normally-exposed, and (c) under-exposed.

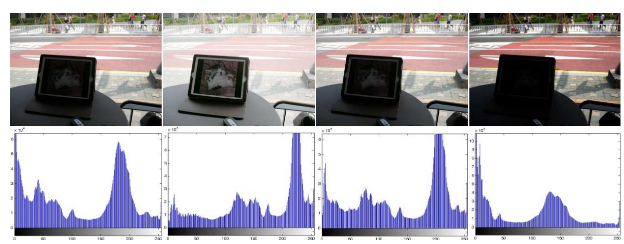
Fig. 3 shows three LDR images captured with moving objects including a moving vehicle and walking pedestrians. Under the dynamic acquisition environment for multiple LDR images, the generated HDR image contains ghost artifacts in non-static regions. Moreover, mobile devices usually have limited memory available for running applications. Furthermore, they must run several applications in parallel which further decreases the available memory space for imaging applications. Since the use of three LDR images is not suitable for mobile devices, the proposed method generates an HDR image using a single input image.



(a) (b) (c)

Fig. 3. Three LDR images captured sequentially with a certain temporal interval; (a) the normally exposed image without any vehicles, (b) the over-exposed image with a white car appearing from the right boundary, and (c) the under-exposed image with a white car proceeding in the center.

In order to overcome the unrealistic restrictions for static acquisition, the proposed method generates three LDR images from a single input image using local histogram stretching as shown in Fig. 4.



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

Fig. 4. Local histogram stretching results with the corresponding histograms; (a) an input reference image, (b) the simulated over-exposed image where bright level histogram is stretched, (c) the simulated normally exposed image where the mid-level histogram is stretched, and (d) the simulated under exposure image where the dark level histogram is stretched.

Since multiple LDR images has exactly the same geometric coordinate, the HDR image generated by the proposed method is inherently free from ghost artifacts and significantly reduces the computational complexity because it does not need any image stabilization and image registration.

In order to generate three LDR images from a single input image, the proposed local histogram stretching method first estimates an appropriate stretching region using the WHS method originally proposed by Pei [10]. WHS is constructed based on the data separation units (DSUs), which separate the dataset into two subsets. Let H be a dataset and $H(p)$ the p-th value of the dataset. Here, H will be considered the luminance histogram of the gray level image. The first step of data separation is to set a threshold τ, which is defined as

$$\tau = \underset{0 \le t < H}{\operatorname{argmin}} \left| w - \frac{1}{M} \sum_{p=0}^{t} H(p) \right|, \tag{1}$$

where w represents a weighted factor to control the sizes of two separated subsets. The variable M denotes the total number of the data points in H, and is defined as

$$M = \sum_{p=0}^{L-1} H(p), \tag{2}$$

where L represents the dimension of H, which is equal to 256 for the luminance histogram.

Using the specified threshold τ we split H into two subsets H_0 and H_1, which are defined as

$$H_0(p) = \begin{cases} H(p), & if \quad p \le \tau \\ 0, & otherwise \end{cases} \quad and \quad H_1(p) = \begin{cases} H(p), & if \quad p > \tau \\ 0, & otherwise \end{cases}. \tag{3}$$

If we split histogram H into two subsets by using τ, each subset contains bright levels from 0 to τ and from τ to 255. Therefore, we can acquire different exposed LDR images by stretching each subset.

The proposed method transforms the RGB color space to the hue, saturation, and value (HSV) color space, and stretches the histogram of the V channel in the following manner.

$$\hat{S}_i(x,y) = \frac{S_i(x,y) - \min\limits_p H_i(p)}{\max\limits_p H_i(p) - \min\limits_p H_i(p)} \times 255, \; for \;\; i \in \{0,1\}, \tag{4}$$

where $S_i(x,y)$ is the pixel intensity at (x,y) in subset image i. The histogram stretched V channel, together with the unprocessed H and S channels, is then transformed back to the RGB color space.

The stretched histogram H_0 belongs to the over-exposed image, and H_1 belongs to the under-exposed image. Finally, we can finally fuse these three LDR images, the reference, under-exposed, and over-exposed images, to generate the HDR image.

B. Edge-Preserving Spatially Adaptive Denoising

During the local histogram stretching process, noise is amplified together with the brightness levels, and consequently degrades the quality of the HDR image. To reduce this noise, the simplest approach would be to use an averaging filter. However, this method removes not only noise but also important details such as edges. In order to remove noise while preserving the edges, the proposed method employs a spatially adaptive denoising algorithm that takes detailed high-frequency regions from a noisy LDR image and takes flat regions from the result of averaging filter with an appropriate amount of weighting between the two as follow:

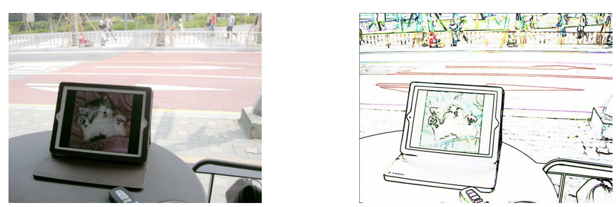
$$\hat{g}(x,y) = \left[\left\{ 1 - \alpha(x,y) \right\} \times \hat{S}(x,y) \right] + \left[\alpha(x,y) \times g(x,y) \right], \tag{5}$$

where g is the output of averaging filter. The parameter α is a weighting factor that is given by

$$\alpha(i,j) = \frac{1}{1 + \theta\sigma^2}, \tag{6}$$

where σ^2 represents the local variance, and θ represents a tuning parameter to make α distributed as uniformly as possible in the range of [0,1].

Fig. 5(a) shows the histogram stretched image with amplified noise and Fig. 5(b) shows the corresponding color-mapped edge image, where black regions represent edge that are common in all three color channels, and white regions correspond flat, non-edge regions. If there is, for example, an edge in the R channel, then the corresponding region will be red.



(a) (b)

Fig. 5. (a) A histogram stretched image with amplified noise and (b) the corresponding color-mapped edge image.

Each RGB histogram stretched image is processed by the denoising algorithm given in (5). The denoised HDR images will be shown in the following section.

C. LDR Image Fusion

Mobile image devices have limited computational power and available memory, which makes multi-frame HDR difficult. For efficient implementation, the proposed fusion process uses only simple arithmetic operations for the limited number of images. More specifically, the proposed HDR method generates three LDR images from a single input image.

Bilcu's method first fuses two LDR images out of three, then the result of fusion and the third image are fused again. Such repetitive approach aims at reducing memory space at the cost of processing time. On the other hand the proposed method fuses three LDR images at one time, as follows

$$H_c(i,j) = \frac{\sum_{k \in \{O,N,U\}} I_c^k(i,j) W(Y_c^k(i,j))}{\sum_{k \in \{O,N,U\}} W(Y_c^k(i,j))}, for\ c \in \{R,G,B\}, \quad (7)$$

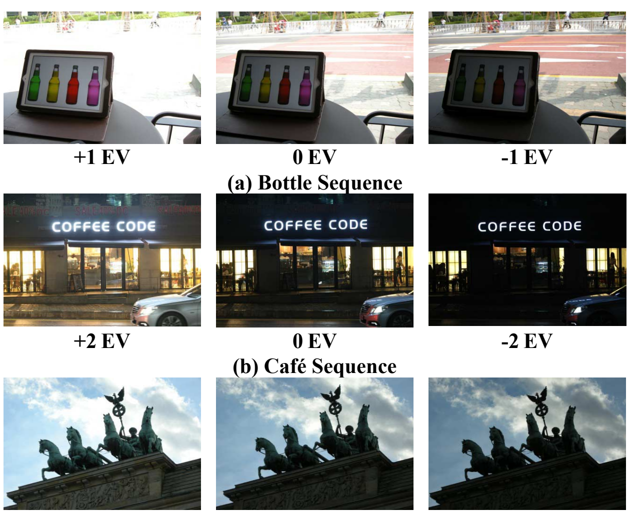
where H_c represents the HDR image, and I_c^k, $k \in \{U,N,O\}$, represent locally contrast stretched LDR images simulating under-, normally-, and over-exposed images, respectively. The weighting factor $W(Y_c^k)$ is a function of Y_c^k that represents each LDR image. The weighting factor is computed by using Gaussian-shaped function, which is defined as

$$W(x) = \frac{10}{p} \exp\left(\frac{(x-127.5)^2}{127.5^2} \times 0.5 \right), \quad (8)$$

where p represents a normalizing constant.

III. Experimental Results

In the experiment, we used three sets of images called Bottle, Café, and Berlin of size 2592×1944. Each set consists of three LDR images acquired by different exposure values (EVs) in the presence of camera and objects motion as shown in Fig. 6.

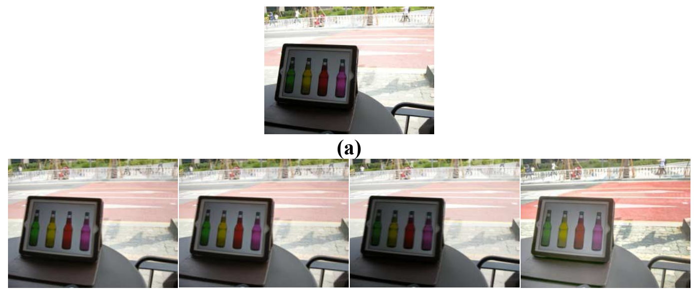


+1 EV 0 EV -1 EV
(a) Bottle Sequence
+2 EV 0 EV -2 EV
(b) Café Sequence
+1 EV 0 EV -2 EV
(c) Berlin Sequence
Fig. 6. Three sets of test images.

In the set of Bottle images the camera is shaking, and pedestrians are walking as shown in Fig. 6(a). In the set of Café images both the camera and the vehicle are moving in different directions as shown in Fig. 6(b). In the set of Berlin images the camera is shaking under backlighting environment as shown in Fig. 6(c).

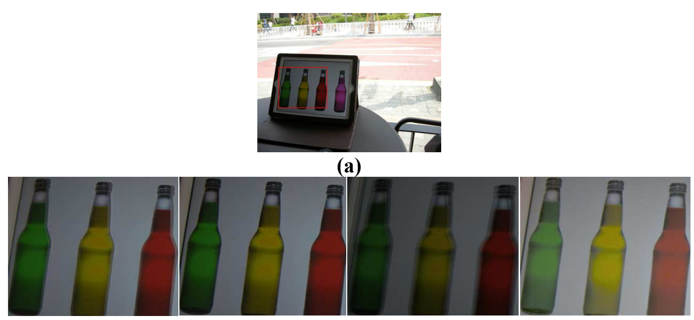
0 EV 0 EV -2 EV
(a) Bottle sequence (b) Café sequence (c) Berlin Sequence
Fig. 7. Three test images for the proposed method.

We compare the proposed single image-based HDR method with Debevec's [3], Im's [8], and Bilcu's [9] methods. Three existing methods generate HDR images using the set of three LDR images as shown in Fig. 6. On the other hand, the proposed method generates HDR images using a single input image as shown in Fig. 7.



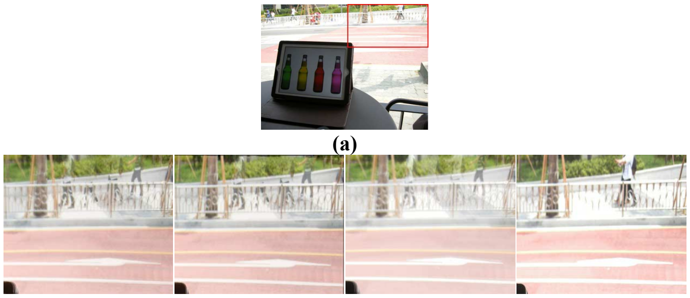
(a)
(b) (c) (d) (e)
Fig. 8. Experimental results comparing different HDR methods (Bottle Sequence); (a) Input image, (b) Debevec's method, (c) Im's method, (d) Bilcu's method, and (e) the proposed method.

Fig. 8 shows estimated HDR images using five different HDR methods. Fig. 8(a) represents the input image, and Figs. 8(b)-(e) represent estimated HDR images using five different HDR methods. We can find that all method successfully enhance contrast in the road and sidewalk region. However, because the input LDR images are captured in presence of camera and object motion, the results of existing methods contain ghost artifact.



(a)
(b) (c) (d) (e)
Fig. 9. A cropped and enlarged region of the Bottle image; (a) Input image, (b) Debevec's method, (c) Im's method, (d) Bilcu's method, and (e) the proposed method.

The cropped and enlarged versions of the Bottle image are shown in Fig. 9 and Fig. 10, respectively. In Fig. 9, Debevec's and Bilcu's result exhibits ghost artifacts whereas Im's method can remove ghost artifacts because of its global motion estimation and compensation function as shown in Fig. 9(b), Fig. 9(c), and Fig. 9(d), respectively. In contrast to three existing methods, the estimated HDR image by the proposed method is free from ghost artifacts and amplified noise as shown in Fig. 9(e).

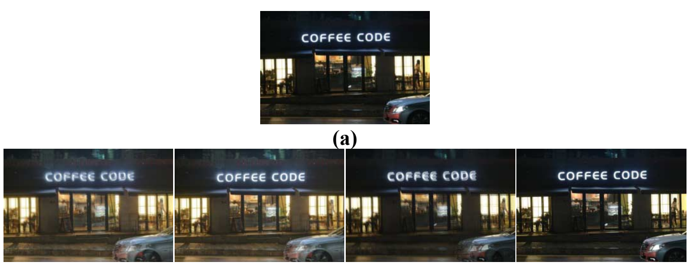


(a)

(b) (c) (d) (e)

Fig. 10. Another cropped and enlarged region of the Bottle image; (a) Input image, (b) Debevec's method, (c) Im's method, (d) Bilcu's method, and (e) the proposed method.

Fig. 10 shows experimental results in another cropped region. We can find that three existing methods contain ghost artifacts as shown in Fig. 10(b), Fig. 10(c), and Fig. 10(d), respectively. Because Debevec's and Bilcu's methods cannot compensate relative motion between the camera and objects, they generate ghost artifacts. Although Im's method can compensate global motion, such as camera motion, it cannot compensate local motions, such as walking pedestrians. Therefore, ghost artifacts are generated in the region containing moving objects. On the other hand, the estimated HDR image by the proposed method is free from ghost artifacts and amplified noise.



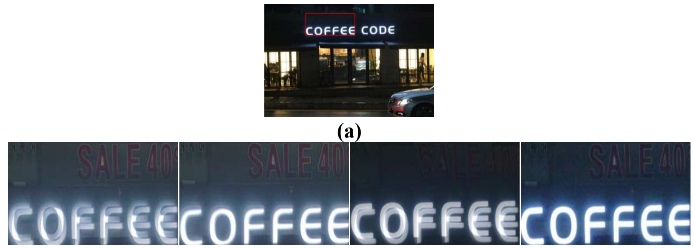
(a)

(b) (c) (d) (e)

Fig. 11. Experimental results comparing different HDR methods (Café Sequence); (a) Input image, (b) Debevec's method, (c) Im's method, (d) Bilcu's method, and (e) the proposed method.

Fig. 11 shows estimated HDR images of the Café sequence. Because Café sequence is acquired in the presence of both camera's and object's motions, the results of all three existing methods cannot avoid ghost artifacts as shown in Fig. 11(b), Fig. 11(c), and Fig. 11(d). On the other hand, the proposed method can expand dynamic range without ghost artifacts or amplified noise as shown in Fig. 11(e).

Café sequence is cropped and enlarged for clearer comparison as shown in Fig. 12 and Fig. 13. Because Debevec's and Bilcu's method cannot compensate camera motion, ghost artifact is prevailing as shown in Fig. 12(b) and Fig. 12(c), respectively. Although Im's method can compensate the global camera motion, ghost artifact still remains as shown in Fig. 12(d). The proposed method can significantly reduce noise without ghost artifacts as shown in Fig. 12(e).

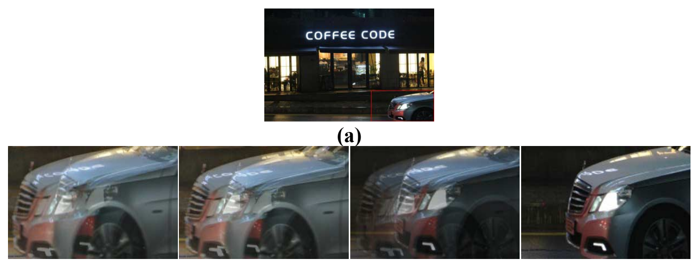


(a)

(b) (c) (d) (e)

Fig. 12. A cropped and enlarged region of the Café image; (a) Input image, (b) Debevec's method, (c) Im's method, (d) Bilcu's method, and (e) the proposed method.

Fig. 13 shows estimated HDR images in another cropped region. Because the vehicle is moving, local motion exists. Therefore, Debevec's, Bilcu's, and Im's methods generate ghost artifacts as shown in Fig. 13(b), Fig. 13(c), and Fig. 13(d), respectively. On the other hand, the proposed method generates the HDR image without amplified noise and ghost artifacts as shown in Fig. 13(e).

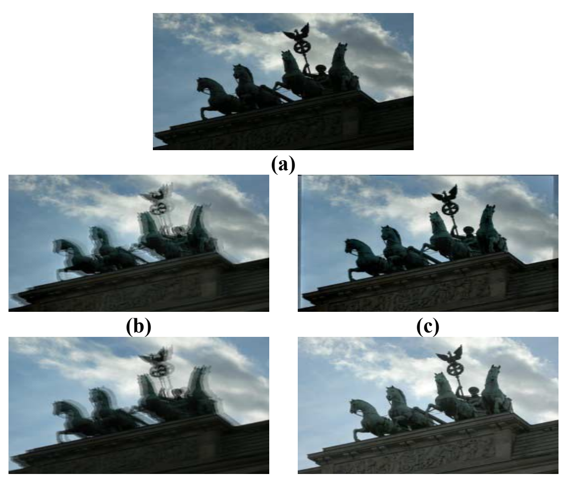


(a)

(b) (c) (d) (e)

Fig. 13. Another cropped enlarged region of the Café image; (a) Input image, (b) Debevec's method, (c) Im's method, (d) Bilcu's method, and (e) the proposed method.

Fig. 14 shows estimated HDR images of Berlin sequence, and produces the similar results shown in Fig. 13.



(a)

(b) (c)

(d) (e)

Fig. 14. Experimental results comparing different HDR methods (Berlin Sequence); (a) Input image, (b) Debevec's method, (c) Im's method, (d) Bilcu's method, and (e) the proposed method.

Fig. 15 shows cropped regions for comparing results with and without denoising.

(a) (b)

Fig. 15. A cropped regions for edge-preserving spatially adaptive denoising results; (a) Bottle sequence and (b) Café sequence.

Fig. 16(a) and Fig. 16(d) respectively represent color mapped edge image of Bottle and Café sequences. Fig. 16(b) and Fig. 16(e) represent noisy HDR image, which are generated by fusing noisy three LDR images. The finally denoise versions are shown in Fig. 16(c) and Fig. 16(f), respectively.

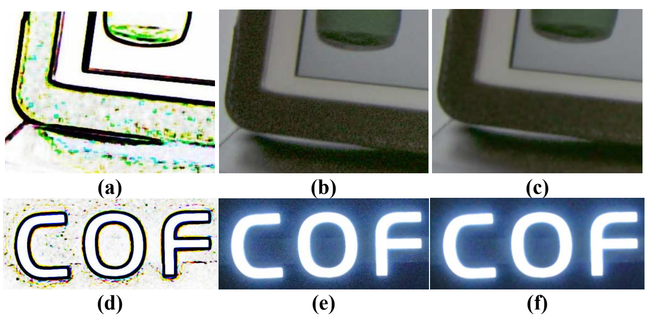
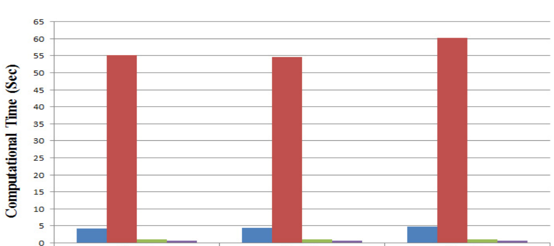


Fig. 16. The result of denoising by using edge-preserving spatially adaptive denoising method; (a) color edge map of the Bottle images, (b) noisy HDR image, (c) result of denoising, (d) color edge map of the Café images, (e) noisy HDR image, and (f) result of denoising.

Fig. 17 shows the processing time of four HDR methods. Debevec's method cost about 4 second to generate HDR image. On the other hand, because Im's method contains the iterative registration step, it took over 50 second. Since Bilcu's method has been proposed for mobile applications, it took approximately 1 second to generate HDR image. On the other hand, the proposed method fuses all LDR images at a time. Therefore, the proposed method can generate HDR image twice faster than Bilcu's method by taking approximately 0.4 second.



	Café	Bottle	Berlin
Debevec's method	4.26	4.36	4.72
Im's method	55.26	54.58	60.25
Bilcu's method	1.14	1.12	1.11
Proposed method	0.74	0.71	0.7

Fig. 17. Processing time of four HDR methods.

IV. Conclusions

We proposed a novel single image-based ghost-free HDR method using local histogram stretching and edge-preserving spatially adaptive denoising. Because the existing multiple frame-based HDR methods work only on condition that there is no camera and object movement when acquiring multiple, differently exposed LDR images, ghost artifact is unavoidable in the dynamic environment. For solving this problem, the proposed method self-generates three LDR images from a single input image using local histogram stretching. For suppressing noise amplification during the histogram stretching process, we also propose an edge-preserving spatially adaptive denoising algorithm. We can then generate HDR image by fusing three local histogram stretched and noise reduced LDR images. The proposed method can generate ghost artifact-free HDR images using a single input image. For this reason the proposed method provides easy acquisition using a consumer camera without using a tripod for acquiring LDR images, and can be applied to mobile phone cameras and consumer compact cameras to provide the ghost artifacts-free HDR function in the form of either embedded or post-processing algorithms.

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