Multiple Exposure Integration with Image Denoising

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***Abstract*—We propose a denoising technique for multiple exposure image integration. In our method, noise removal is achieved by the wavelet-shrinkage for multiple exposures, and a novel weighting scheme for the integration. A weighted image is converted to the low and the high frequency elements by the shift invariant wavelet transform, and the wavelet coefficient in the high frequencies are decreased by thresholding based on the wavelet-based hard shrinkage. The weight is designed to reduce sensor noise and quantization noise in the process of the multiple exposure integration. Our method works well especially for noise in shadow areas. We show the validity of the proposed algorithm by simulating the method with some actual noisy images.**

***Index Terms*—Image denoising, Exposure fusion, Wavelet shrinkage, Weighting function**

I. Introduction

By adapting to lights in any viewing condition, the human visual system (HVS) can capture a wide dynamic range of irradiance (about 14 orders in log unit), while the dynamic range of CCD or CMOS sensors in most of today's cameras does not cover the perceptional range of real scenes. It is important in many applications to capture a wide range of irradiance of natural scene and store the irradiance value in each pixel. For example, it can address the problem of under- or over-exposure when taking a photo of a man with very bright backlight, or photographing outside from a tunnel. In the application of CG, a high dynamic range image (HDRI) is widely used for high quality rendering with image based lighting [1]. In addition, it is applied to the car-mounted camera, the surveillance camera, and the photographic development with high resolution.

In the last decade, to capture the HDRI, many techniques have been proposed based on the multiple-exposure principle, in which the HDRI is constructed by merging some photographs shot with multiple exposures. To gain high dynamic range, we should take several photographs with short to long exposures. The dynamic range is generally defined by the ratio of darkest and brightest intensities of an image, where the darkest point is usually defined as the lowest value in a range that is not dominated by noise. Images captured by image sensors generally suffer from the noises such as dark current and shot noises. Thus the image denoising is often required to acquire the high dynamic range. The merging process of multiple exposures inherently has capability to reduce the noise. However it is inadequate and noises often appear especially in shadows. Especially when taking photos with a hand held camera under a dark lighting condition, high ISO setting is required to restore the dark area without blurring artifacts, which yields noisy images and then brings down the dynamic range. Moreover the dark area of the HDR is enhanced by tone mapping operators. Many of the existing operators tend to stretch the dark area to enhance the local contrast in shadows, which makes the noise more perceivable. Moreover this property of the tone mapping often emphasizes quantization noise. Most of conventional methods for the HDR image integration [2]-[5] do not take the noise into account, in which multiple images are merged simply by taking a weighted mean. The summation of multiple images inherently has the denoising property, but its effect is not very effective.

In this paper we propose an integration technique of the multiple exposure images. In our method, the noise removal is achieved by the wavelet-shrinkage for multiple exposures and a novel weighting scheme for the integration. A weighted image is converted to the low and the high frequency elements by the shift invariant wavelet transform, and the wavelet coefficients in the high frequencies are decreased by thresholding based on the wavelet-based shrinkage. The weight is designed to reduce sensor noise and quantization noise in the process of the multiple exposure integration. Our method works well especially for noise in shadow.

In the following section, we introduce a technique for combining the multiple exposure images. In the method, the image is combined in the wavelet domain. By employing a sparse approximation in the wavelet expansion, the denoising is fulfilled. In Section III, a new weighting scheme is introduced to further reduce the sensor noise and quantization error. In Sec. IV, we show some examples to show the validity of the algorithm.

II. Proposed Method

A. Outline

Figure 1 shows the block diagram of the proposed technique. We take multiple exposure images as an input. For a color image, the same process is employed to each of RGB channels. First of all, the input images are converted to radiance domain by compensating the nonlinearity of a sensor to linearize the response. A weighting function, which is designed to minimize the error, is multiplied to each of the images. Then, they are transformed by the shift invariant wavelet decomposition. In the wavelet domain, the multiple images are combined after the hard shrinkage is performed for the wavelet coefficients. The HDR image is restored simply by

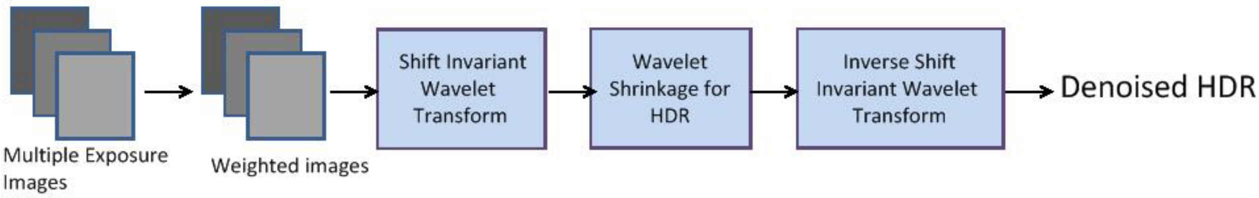

Fig. 1. Block diagram

the reverse shift invariance wavelet transform. Detail of each step is explained in the following sections.

B. Image Integration

The relationship between the irradiance R and the amount of lights L that we measure through some sensor can be expressed by [4]

$$L = R \cdot t, \tag{1}$$

where t is a exposure time.

In many of camera sensors, the captured signal L is nonlinearly transformed to pixel values i. In practice, the pixel i is one of the observed RGB values at a pixel, which is typically quantized to 8 bits. For convenience, we set the range of i to [0, 1]. To accurately retrieve the irradiance, we need to compensate the nonlinearity by estimating the transform. Here we call the transform "camera response curve" and we denote it by

$$i = g(L) \tag{2}$$

Among the existing methods for the camera calibration problem, we adopt Mitsunaga et al.'s method [4] to find g, in which the curve is approximated by a low order polynomial using multiple images and the values of exposure ratios between the images. Once the curve is estimated the irradiance is derived from (1) and (2) as

$$R = f(i)/t \tag{3}$$

where the inverse camera response curve, $f(x) = g^{-1}(x)$. In our method, the multiple exposure images are taken by varying the shutter speed of a camera with other settings fixed.

In the conventional methods [2]-[5], the irradiance R of each multiple exposure image is calculated by (3), it is merged by taking a weighted mean in conventional methods,

$$I_m = \frac{\sum_{n=1}^{N} w\left(n\right)\left[R_m\left(n\right)/t_n\right]}{\sum_{n=1}^{N} w\left(n\right)}, \tag{4}$$

where $R_m(n)$ is a $m = \{R, G, B\}$ channel of the n-th exposure image. N is the number of images, t_n is the exposure time of the n-th image, and w is a weighting function.

In our method, the integration is performed in the wavelet domain. We first apply the weighting function to R_m before the wavelet transform:

$$R'_m(n) = w(n) \cdot R_m(n). \tag{5}$$

Detail of the weight w is explained in the next section. Then the weighted image is transformed by the Haar-based shift invariant wavelet. The integration is performed to R'_m in the wavelet domain.

C. Denoising by Shrinkage

In general, a low exposure yields a dark image and its low pixel values with noises are enhanced by the camera response curve and the tone mapping operator. Summing up multiple images may remove the noise to some extent, since such noises randomly appear. However the simple integration (4) does not always remove noises adequately. In this section we try to remove the noise by using the shrinkage.

We apply the wavelet shrinkage to our integration problem to remove the noise. The weighted image, R'_m in (5) is converted by the Haar-based shift invariant wavelet transform, that is, a wavelet decomposition without subsampling. In the wavelet conversion, a low-pass filter (L) and high-pass filter (H) are performed to it in the horizontal and vertical direction respectively, and four subbands (LL, HL, LH, and HH) are produced, and then repeatedly the LL band is transformed to four bands. The wavelet shrinkage is a process to make the wavelet representation sparse by thresholding the wavelet coefficients.

Here we introduce the wavelet shrinkage for the multiple exposure fusion. In our method, we modify the shrinkage [7], [8] to a multiple exposure integration. The problem is defined to minimize the cost function:

$$\min_h E(h) = |h|^0 + \lambda \sum_{n=1}^{N} (h - h(n))^2, \tag{6}$$

where $h\left(n\right)$ is an input wavelet coefficient of the weighted n-th exposure image and h is an output wavelet cofficient formed by the high dynamic range. By differentiating $E(h)$ with respect to h and setting it to 0, we derive the optimal wavelet coefficients:

$$h^* = \begin{cases} 0, & if \quad 1 - \lambda \left(\frac{1}{N}\sum_n h(n)\right)^2 > 0 \\ \frac{1}{N}\sum_n h(n), & otherwise \end{cases}. \tag{7}$$

The scaling coefficients are simply merged by the weighted mean (4). Note that roles of are not only the shrinkage based denoising but also multiple exposure fusion in the wavelet domain in which it is different from the conventional shrinkage.

III. Weighting Function

A. conventional scheme

In the conventional methods the weighting function is introduced because under- or over- exposed regions are much less reliable than the regions of middle intensities. Thus in the conventional methods, the weight is specified to be small for pixel values of the saturated regions, high for the middle intensities. Two examples for the weighting functions used in the conventional methods [2] , [3] are shown in Fig.2.

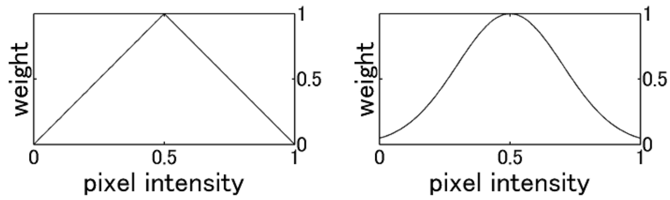

Fig. 2. Two examples of weighting functions: (left) hat function, (right) Gamma-like function

In the conventional methods, the weighting functions in Fig.2 are built based on the assumption that middle intensities around 0.5 have high reliability for irradiance estimation.

B. Weight for denoising

The noise occurred in CCD and CMOS sensors are in general well characterized by the additive signal-dependent and independent terms [6], then we model the noise by

$$L = x + a_1\delta_1 + a_2\delta_2 x, \tag{8}$$

where x and L are the noiseless signal and output of the sensor, respectively. δ_1 and δ_2 are Gaussian noises and a_1 and a_2 are parameters that characterizes the sensor.

In most cameras, an image compression is performed in the end of pipeline, and thus the quantization error δ_q is added to $g(L)$. Then the output of the camera compensated by the inverse camera response curve can be written by

$$f(g(L) + \delta_q),$$

By approximating the output by the linear function of δ_q, the noise term is denoted by

$$\begin{aligned} f(g(L)+\delta_q) - x &\approx f(g(L)) + f'(g(L))\delta_q - x \\ &= L + f'(g(L))\delta_q - x \\ &= a_1\delta_1 + a_2\delta_2 x + f'(g(L))\delta_q \end{aligned} \tag{9}$$

In an ideal case where the effect of the camera response curve g is completely canceled by the inverse operation f in Sec. II-B, the noise is derived by

$$n = (a_1\delta_1 + a_2\delta_2 x + f'(g(L))\delta_q)/t. \tag{10}$$

In our method, the weighting function should be designed to the inverse of the noise.

$$\begin{aligned} w_0(i) &= m(i)\cdot\frac{1}{(a_1\delta_1 + a_2\delta_2\cdot x + f'(g(L))\delta_q)/t} \\ &\approx m(i)\cdot\frac{1}{(a_1\delta_1 + a_2\delta_2\cdot L + f'(g(L))\delta_q)/t} \\ &= m(i)\cdot\frac{1}{(a_1\delta_1 + a_2\delta_2\cdot f(i) + f'(i)\delta_q)/t} \end{aligned} \tag{11}$$

where $m(i)$ is a masking function that decays to 0 at $i = 0$ and $i = 1$, and we use the approximation $x \approx L$. In practice, however, determining the parameters a_1, a_2 and the means of the noises δ_1, δ_2, δ_q are usually laborious task. Thus we simply Eq.(11) by

$$w(i) = m(i)\cdot\frac{1}{(b_1 + b_2 f(i) + b_3 f'(i))/t} \tag{12}$$

The parameters b_1, b_2, b_3 are determined by trial-and-error and are fixed for all of images. The first and second terms of (10) are sensor noises, while the third term corresponds to the quantization noise. Thus one can control the suppression effect of the sensor noise and quantization error by varying the parameters in (12).

IV. Experimental Results

In order to evaluate the validity of the proposed algorithm, we have conducted for some examples. In the first experiment, we use three photographs, which are sampled from [9]. Three shots are obtained by changing the shutter speed, while the aperture is fixed, and use them as an input for our algorithm. As a conventional method, we combine the images with the hat type of the weight (Fig.2).

In Fig.3 the results obtained by (lower left) the conventional method and (lower right) our method for two sample images. The contrast is enhanced by the CLAHE-based tone mapping [10] to improve visibility.

Next we show the effect of the weighting function. Fig.4 are the tone-mapped results obtained by our weighting scheme. In order to show the effect of the weight clearly, the shrinkage is not performed to this result. The left image is the result that we put more weights on the sensor noise removal, that is, larger b_1 and b_2 in (12), while the right image is obtained by putting more weights on the quantization noise removal, that is, larger b_3. One can see that our weight can control the suppression effect of the two types of noises.

To evaluate the method quantitatively, we artificially created ground truth and noisy images as follows. Three images with different exposures, each of which is obtained by averaging 20 photographs (set this as a noise free photo), and we added noises to the images. Then the three images are integrated by conventional method or our method. Fig.5 shows of the results. The image at the top is the tone-mapped version of an original (noise free) HDR image. The right and left figures in the bottom are obtained by BM3D [12] and our method, respectively. The SSIM scores [11] of ours and BM3D are comparable (0.97 for both of them). One can see from the

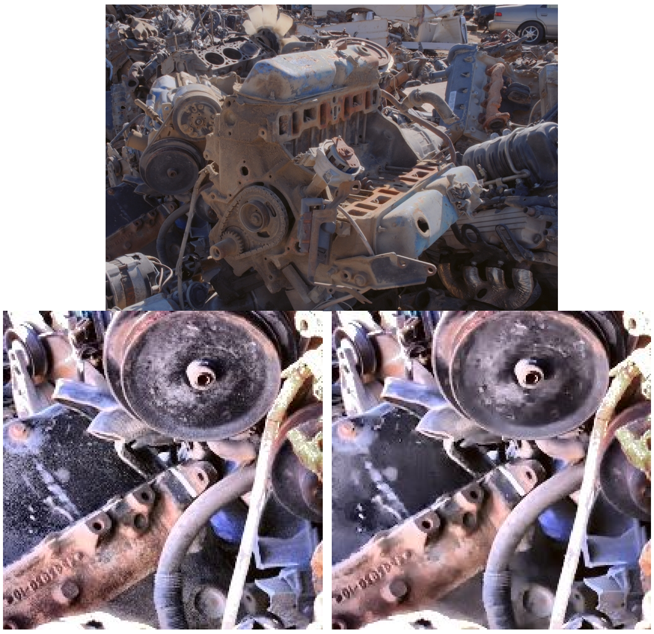

Fig. 3. Examples: (upper) noisy image, (lower left) conventional method, (lower right) our method

Fig. 4. Example 2: (left) sensor noise suppression, (right) quantization noise suppression

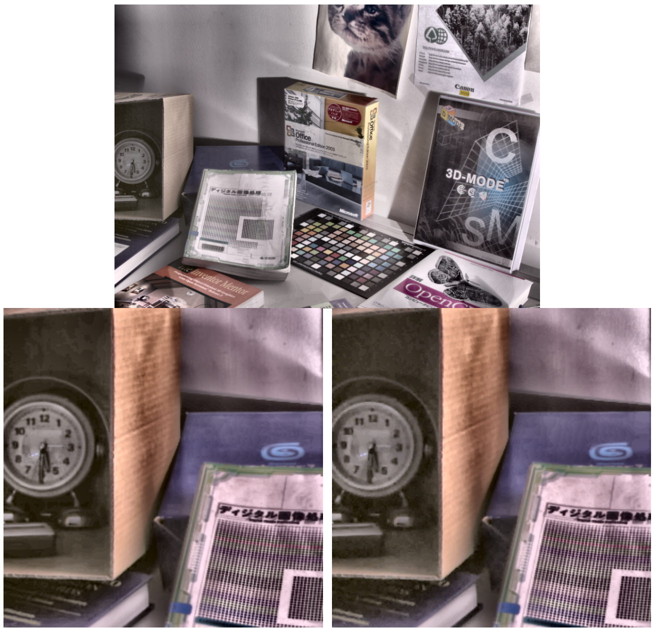

Fig. 5. Example 3: (upper) Ground truth, (lower left) conventional method (BM3D), (lower right) our method

figure, however, that the result of BM3D has slightly clearer contrast. On the other hand, our method is about ten times faster than BM3D, and selectively control the suppression rate of the sensor and quantization noise by (12).

V. Conclusion

We proposed a method for the HDR acquisition with noise removal. The proposed method can significantly reduce noises compared with the conventional integration method, especially in the dark area. Moreover, we proposed the new weighting function that can control the suppression of quantization and sensor errors. In addition, our method can reduce noises with less computational complexity.

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