# NOISE REDUCTION FOR DIFFERENTLY EXPOSED IMAGES

*Wei Yao, Zhengguo Li, Susanto Rahardja*

Signal Processing Department, Institute for Infocomm Research, Singapore.

## ABSTRACT

For scenes under low lighting condition, cameras are usually set to a high sensitivity (ISO) mode to reduce motion blur at the cost of increased image noise. When multiple differently exposed images are used to generate a high dynamic range (HDR) image, the high ISO noise from each low dynamic range (LDR) image can be further amplified by the HDR synthesis algorithm which would result in severely degradation of visual quality. This paper proposes an intensity mapping function based noise reduction method for differently exposed images with high ISO noise. The proposed method does not require any knowledge on either camera response functions or exposure times. In addition, the method is simple yet effective for noise removal from the LDR images without introducing any blurring or other artifacts.

***Index Terms—*** Noise reduction, High dynamic range imaging, Intensity mapping function, Weighted frame averaging

## 1. INTRODUCTION

High Dynamic Range (HDR) imaging is getting more and more popular for its capability in reliable reproduction of real world scenes. An HDR image is usually synthesized by combining several differently exposed shots of a given scene to overcome the dynamic range limitation of traditional single-shot low dynamic range (LDR) image. To take differently exposed LDR images under low lighting condition, cameras are usually set to high ISO settings so as to reduce motion blur. However, high ISO setting increases noise on LDR images, especially in dark areas and therefore degrades the quality of the final synthesized image. Hence, a new technology that has good de-noising capability to construct an HDR image is highly demanded.

Given a set of differently exposed LDR images, there are, in general, two approaches to get a better quality HDR image. One is to combine differently exposed images into a 32-bit HDR image and then tone mapped it back to an 8-bit LDR image so that it can be displayed by any existing digital device [1]-[3]. The other one is to directly fuse all input images into an 8-bit LDR image that preserves more details than any of the input LDR image [6]. The latter is usually much simpler and is suitable for handheld devices such as smart phones and digital cameras. Different de-noise methods can be applied to the aforementioned approaches. When LDR images are combined by a weighted averaging into a 32-bit HDR image, the weighted averaging reduces noise as compared to the noise in each single LDR input image. Several different weighting functions based on different observations have been proposed [1] - [5]. All these weighting functions set zero or small weights to pixels which are either underexposed or overexposed in LDR images. This feature makes these methods work well in removing noise caused by the saturation of camera response function (CRF), i.e., the quantization noise, but not the sensor noise caused by high ISO settings. Moreover, weighted averaging is a step only available in the process of 32-bit HDR synthesis, it cannot be used on exposure fusion. Frame averaging [7] is another useful denoising method when multiple images of the same scene are available. It is a blur free method. However, the intensities of all co-located pixels in multiple images must be the same by the standard frame averaging, which is not applicable to LDR images with different exposures in the case of HDR imaging. Akyuz and Reinhard [8] extended the method to the case of different exposures by conducting standard frame averaging in the HDR domain. In other words, all LDR images are first mapped to the 32-bit HDR domain and frame averaging is carried out on HDR domain, after which each LDR image can be obtained by mapping HDR domain back to LDR domain through CRF. The process of mapping HDR domain back to LDR domain is time consuming and this method requires both the CRFs and the exposures of all LDR images to be known.

In this paper, we propose a new weighted frame averaging in LDR domain with the help of intensity mapping function (IMF) to reduce noise from differently exposed LDR images. All LDR images are first arranged according to their exposure times. Since the knowledge of exposures might not be available in some applications, the average intensity values of an image are adopted in the proposed scheme. Each LDR image is corrected using several successive LDR images with longer exposures in the same sequence. Instead of mapping all LDR images to the HDR domain as in [8], all LDR images with longer exposures are first calibrated according to the image to be de-noised by using the IMFs among them. All mapped LDR images and the image to be de-noised are then averaged with a predefined weighting function to generate the corrected LDR image. With the observation that LDR images with longer exposures include less noise, the weighting function is designed such that higher weights are given to pixels captured with longer exposure times. The noise in the LDR image with a shorter exposure can thus be reduced and the noise in the corresponding areas of synthesized HDR image are also effectively removed.

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## 2. A SIMPLIFIED NOISE MODEL FOR DIFFERENTLY EXPOSED IMAGES

Let $Z_{i,l}(x,y)$ denote the image intensity value of the $l$th color channel at the position $(x,y)$ of image $\mathbf{Z}_i$, i.e. $(x,y)$ is a spatial position, $l$ represents the color channel, and $i$ indexes different exposures. Let $E_l(x,y)$ be the irradiance value corresponding to $Z_{i,l}(x,y)$. Their relationship is

$$Z_{i,l}(x,y) = g_l(E_l(x,y)\Delta t_i + \eta_{q,i,l}(x,y)) + \eta_{f,i,l}(x,y), \quad (1)$$

where $g_l()$ is a camera response function (CRF), which is monotonically increasing and its inverse function is denoted as $g_l^{-1}(\cdot)$. $\eta_{q,i,l}(x,y)$ and $\eta_{f,i,l}(x,y)$ are sensor noise and quantization noise, respectively. For simplicity, we will not distinguish $\eta_{q,i,l}(x,y)$ from $\eta_{f,i,l}(x,y)$ but denote the overall noise by $\eta_{i,l}(x,y)$. Let the variance of $\eta_{i,l}(x,y)$ be $\sigma^2_{i,l,ori}(x,y)$. According to the camera noise model in [8], the relationship between $\sigma^2_{i,l,ori}(x,y)$ and $\Delta t_i$ can be represented as

$$\frac{\sigma^2_{i,l,ori}(x,y)}{\sigma^2_{j,l,ori}(x,y)} \propto \frac{\Delta t_j}{\Delta t_i}. \quad (2)$$

Notice that the values of $\Delta t_i$ and $\Delta t_j$ are not always available. It is desirable to use the differently exposed images directly. It can be shown from Equation (1) that

$$Z_{i,l}(x,y) \geq Z_{j,l}(x,y) \Longleftrightarrow \Delta t_i > \Delta t_j. \quad (3)$$

Let $\bar{Z}_{i,l}$ and $\bar{Z}_{j,l}$ be the average values of $Z_{i,l}(x,y)$ and $Z_{j,l}(x,y)$, respectively. It follows that

$$\bar{Z}_{i,l} \geq \bar{Z}_{j,l} \Longleftrightarrow \Delta t_i > \Delta t_j. \quad (4)$$

From Equations (1) and (4), we obtain

$$\frac{\sigma^2_{i,l,ori}(x,y)}{\sigma^2_{j,l,ori}(x,y)} \propto \frac{\bar{Z}_{j,l}}{\bar{Z}_{i,l}}. \quad (5)$$

Based on the above derivation, it is reasonable to assume that $\sigma_{i,l,ori}(x,y)\bar{Z}^{\gamma}_{i,l}$ is a constant, where $\gamma \in \mathbb{R}$.

## 3. IMF BASED WEIGHTED FRAME AVERAGING

In this section, an IMF based weighted frame averaging for the noise reduction of images with different exposures is proposed. Let $\Lambda_{j,i,l}(z)$ $(0 \leq z \leq 255)$ be the IMFs from image $\mathbf{Z}_{j,l}$ to image $\mathbf{Z}_{i,l}$. It can be computed as

$$\Lambda_{j,i,l}(z) = \frac{\sum_{(x,y)\in\Omega_{j,l}(z)} Z_{i,l}(x,y)}{|\Omega_{j,l}(z)|}, \quad (6)$$

where $|\Omega_{j,l}(z)|$ is the cardinality of set $\Omega_{j,l}(z)$, and $\Omega_{j,l}(z)$ is defined as

$$\Omega_{j,l}(z) = \{(x,y)|Z_{j,l}(x,y) = z\}. \quad (7)$$

To carry out IMF based frame averaging, all the LDR input images are firstly arranged accordingly to exposure times in an ascending order. If exposure times are not known beforehand, the LDR input images can be arranged based on the mean of pixel intensity values $\overline{Z}_{j,l}$. Each original noisy LDR input image is corrected by using several successive images with longer exposures in the sequence. Suppose there are $N$ input LDR images and the image to be de-noised is $Z_{i,l}$, the corrected image $\hat{Z}_{i,l}(x,y)$ at exposure $i$, $i \in [1,N]$, on color channel $l$ is computed by using an IMF based weighted frame averaging method as

$$\hat{Z}_{i,l}(x,y) = \frac{\sum_{j=i}^{i+\zeta} \tilde{Z}_{j,l}(x,y)\cdot W_j(Z_{j,l}(x,y),\bar{Z}_{j,l})}{\sum_{j=i}^{i+\zeta} W_j(Z_{j,l}(x,y),\bar{Z}_{j,l})}, \quad (8)$$

where $\zeta$ is a window size, $\tilde{Z}_{j,l}(x,y)$ is the IMF mapped image from exposure $j$ to exposure $i$ and it is defined as:

$$\tilde{Z}_{j,l}(x,y) = \begin{cases} Z_{i,l}(x,y) & \text{if } j = i \\ \Lambda_{j,i,l}(Z_{j,l}(x,y)) & \text{if } j \neq i \end{cases}. \quad (9)$$

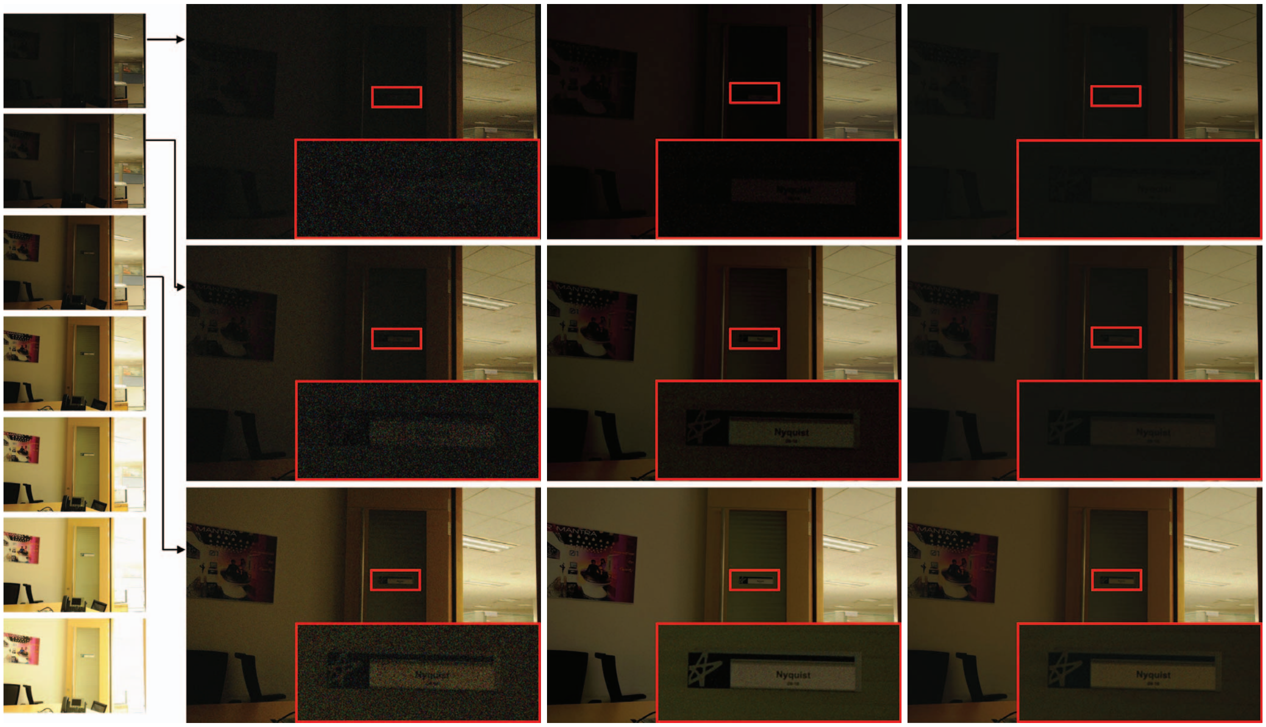
$W_j(z_l,\bar{Z}_{j,l})$ is the weighting function that represents the reliability of the pixel $Z_{j,l}(x,y)$. It depends on both pixel values and the mean of pixel values, which is equivalent to exposure time, of each image. As indicated in [8], averaging with over-exposed pixels may give a "washing out" appearance to the final image. Thus, pixels larger than 249 are excluded from the averaging as [8]. In addition, the weighting function is also designed such that more weights are given to pixels captured with longer exposure times because long exposures tend to have less noise than short exposures. Therefore, the weighting function is defined in following equation:

$$W_j(Z_{j,l}(x,y),\bar{Z}_{j,l}) = \begin{cases} w_{1,j}(\bar{Z}_{j,l}) & \text{if } j = i \\ w_{1,j}(\bar{Z}_{j,l})w_{2,j}(Z_{j,l}(x,y)) & \text{if } j \neq i \end{cases}, \quad (10)$$

where $w_{1,j}(\bar{Z}_{j,l})$ is to utilize the reliability of co-located pixels from differently exposed LDR image, and it is given as

$$w_{1,j}(\bar{Z}_{j,l}) = \bar{Z}_{j,l}. \quad (11)$$

The function of $w_{2,j}(Z_{j,l}(x,y))$ is to address the challenging problem that there is possible large reliability variation among pixels in image $Z_{j,l}$ due to the high dynamic range of a real



(a) Noisy input image (b) De-noised by method [8] (c) De-noised by proposed method

**Fig. 1**. De-noise performance comparison on LDR images. (a) Whole set of input noisy images. Exposures of three images under comparison are 1/20 sec, 1/10 sec and 1/5 sec. (b) De-noised result by method [8]. (c) De-noised result by proposed method. (Readers please zoom in the full-size figures on the electronic version of this paper to better appreciate the differences among images.)

world scene and the low dynamic range of $Z_{j,l}$. $w_{2,j}(z)$ is defined as [8]

$$w_{2,j}(z) = \begin{cases} 1 & 0 \leq z < 200 \\ 1 - 3h^2(z) + 2h^3(z) & 200 \leq z < 250 \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

$$h(z) = \frac{z}{50} - 4. \quad (13)$$

## 4. EXPERIMENTAL RESULTS

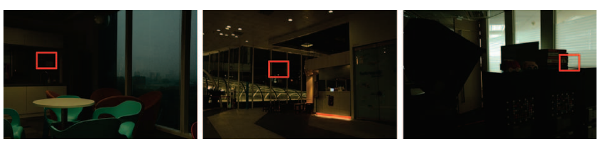
Experiments have been conducted on four image sets to evaluate the performance of the proposed de-noising algorithm. All of the ground truth images were captured using Nikon D300 and each image set includes 7 LDR images with varying exposures at an increment of 1 exposure value (EV). Gaussian zero mean white noise is added to the ground truth images to simulate the sensor noise. Based on Equation (5), the variances of noise added in each image are different. Gaussian noise with the smallest variance 0.001 was added to the brightest image (e.g. longest exposure), and the variance was increased at a rate of 1.5 on each of the following images with short exposures.

Exposure fusion [6] is an approach to directly merge LDR images without any intermediate steps of 32-bit HDR synthesis. The effectiveness of noise reduction on each input LDR images largely determines the quality of final exposure fused image. We thus compared the de-noising performance of the proposed method and the state-of-art method [8] on noisy LDR image sets. Table 1 shows the peak signal-to-noise ratio (PSNR) comparison between the two methods on 4 image sets. It can be seen that, the proposed method in general outperforms [8] but method [8] achieves better PSNR in some of images captured at shortest exposures. Due to the limited

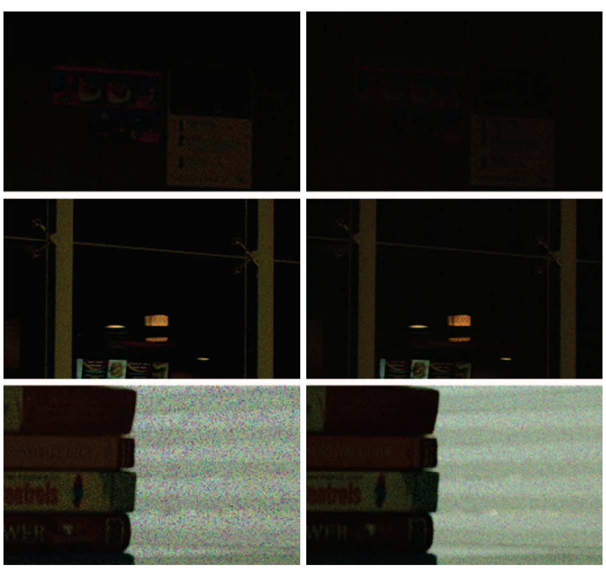
**Table 1**. PSNR comparison between the proposed method and [8].

| Image set | Method | -3EV | -2EV | -1EV | 0EV | 1EV | 2EV |
|---|---|---|---|---|---|---|---|
| ‘Nyquist’ | [8] | 29.26 | 27.26 | 25.38 | 26.54 | 28.73 | 29.94 |
| | Proposed | 28.44 | 29.91 | 30.26 | 29.83 | 30.21 | 30.49 |
| ‘Pantry’ | [8] | 28.68 | 27.46 | 27.01 | 27.50 | 28.83 | 29.96 |
| | Proposed | 30.30 | 31.44 | 30.97 | 30.10 | 29.58 | 30.19 |
| ‘Lab’ | [8] | 27.00 | 26.33 | 26.88 | 28.47 | 29.60 | 29.28 |
| | Proposed | 26.83 | 27.94 | 28.75 | 30.27 | 31.60 | 31.53 |
| ‘Yakun’ | [8] | 28.71 | 26.39 | 25.93 | 27.40 | 28.44 | 29.20 |
| | Proposed | 29.20 | 29.90 | 29.55 | 29.53 | 29.99 | 29.70 |

space of this paper, we can only show one set of testing images, 'Nyquist' in this case, and three images from the sequence with the shortest exposures are displayed in Fig. 1 for performance comparison. Readers are invited to zoom in the full-size figures on the electronic version of this paper to better appreciate the differences among images. Left column of Fig. 1 are the input differently exposed noisy images with varying variances. Images in middle column are the results of method [8] and right most column are the results of the proposed method. The area highlighted by red box are zoomed in on each image for a clearer comparison. The results indicate that both methods can effectively remove noise from input images. The texture of images de-noised by the proposed method are generally more smooth and the contrast at dark area is also higher as compared to method [8]. For other three sets of testing images, we chose one exposure from each set and only a zoomed in cropped area from each image was compared in Fig. 2. First row shows the exposure chosen from sequence 'Pantry', 'Yakun' and 'Lab', respectively. Left column shows the cropped areas from the three images de-noised by method [8]. Right column is the corresponding parts done by proposed method. Consistent results can be seen in Fig. 2. The proposed method obtains a better contrast at dark areas and the de-noise at bright area is also more effective.



(a)



(b) (c)

**Fig. 2**. (a) Selected exposure from 'Pantry', 'Yakun' and 'Lab'. (b) Cropped areas de-noised by method [8]. (c) Cropped areas de-noised by proposed method.

## 5. CONCLUSION

An intensity mapping function based weighted frame averaging method is proposed to reduce noise from the differently exposed images in this paper. The proposed algorithm neither require any information on the camera response functions nor exposure times of input images. It is thus also applicable to a set of images with the same exposure. Meanwhile, it is effective to remove sensor noise and improve the sharpness in dark areas without introducing any blur artifacts, which in turn removes the noise in the dark areas of synthesized HDR images.

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