Local Signal-Dependent Noise Estimation on Texture Domain for CFA Raw Images

Kyu-Ho Lee and Jong-Ok Kim
School of Electrical Engineering, Korea University
145, Anam-ro, Seongbuk-gu, Seoul, Korea
E-mail: {khlee8813, jokim}@korea.ac.kr

Abstract: In this paper, we propose a method of signal-dependent noise estimation and denoising that operates on the CFA (color filter array) raw image. The proposed method effectively deals with signal dependent noise by estimating and denoising on the texture domain in a CFA LR (low resolution) component-wise and localized manner. The proposed method is practically evaluated on a simulated end-to-end imaging pipeline. The experimental results indicate that the proposed method indeed efficiently removes signal-dependent noise.

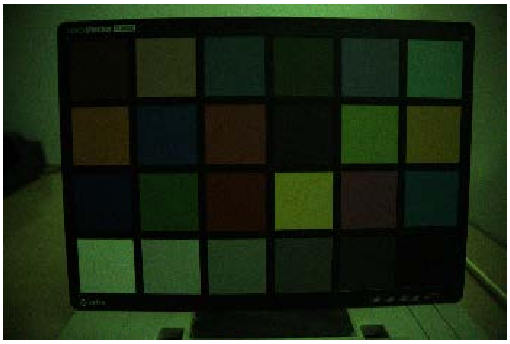
Keywords: image denoising, signal-dependent noise, local noise estimation, CFA raw image.

1. Introduction

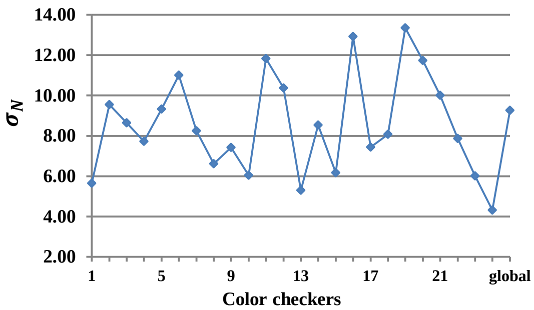
Nowadays it has become fairly easy to obtain high-resolution digital images, thanks to the growth in electronics and camera industries. The demand for high resolution digital cameras is non-decreasing, and is high all the time. Smaller and handy cameras are available, enabling their users to take photographs freely of time and places. When obtaining such an image, noise, which occurs other than the image signal, causes quality deterioration. Digital image noise is known to originate from 5 sources [1]. Especially, in low-light environment, signal dependent noise, among all, is dominant. In such a dim situation, a practical solution to compensate for the deficient brightness is to adjust the ISO level. This means scaling the electrical signal at the CCD sensor level, and through this process not only the image signal but also noise is amplified. Therefore, a large body of research effort is dedicated to denoising the camera capture noise.

As the incident light to the camera through the lens reaches the camera sensor, analog data representing the image is generated. Here, the incident light goes through three color filters matched to the long, middle and short wavelengths to generate the R, G, B digital values. This is to obtain a color image (R, G, B values) using a single CCD, and it is chosen which color value is to be sensed at each location of the CCD. (Although there are 3-CCD cameras that do not use color filters, 1-CCD camera are most popular.) Therefore, the color filter needs to be arranged in a pattern, and most cameras use the Bayer pattern. Using the Bayer pattern, each of the R, G, B color channel images half the resolution of the CCD sensor. The image at this stage is called 'mosaicked,' due to the reason that the three R, G, B channels are incomplete, and they are arranged together in a designated pattern as a single image.

The process needed to generate a full-resolution RGB image using the half-resolution mosaicked image is called 'demosaicking [2].' Demosaicking methods usually assume



(a)



(b)

Figure 1. (a) color checkers in raw image; (b) different level of (signal-dependent) noise for each color checker

that the image is noiseless. Because the image after the Bayer pattern (before demosaicking) is a collection of signal values that has gone through different color filters, neighboring pixels belong to different color component and the noise in those are independent. This implies that there is no correlation between the noises contained in different color components. Because demosaicking methods particularly refer to the neighboring pixels for the purpose of filling in the 'mosaicked' pixels, and thus generating the full-resolution image, demosaicking causes correlation between the noises contained in different color components [3]. This correlated noise is not Gaussian and not event independent (by definition), and therefore difficult to remove. For this reason, denoising must be carried out before the demosaicking step.

Because the noise level of a taken photograph is unknown (blind denoising), it is important to estimate the amount of image noise to obtain reasonable denoising performance. One such method of noise level estimation is [4], which picks out the weakly textured regions of the image, and applies PCA (principal component analysis) to estimate the noise.

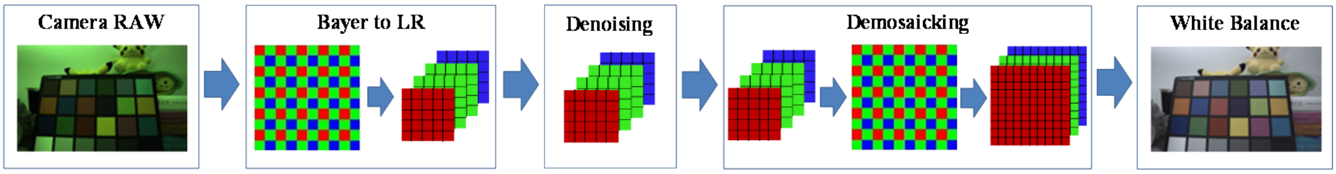


Figure 2. End-to-end imaging pipeline.

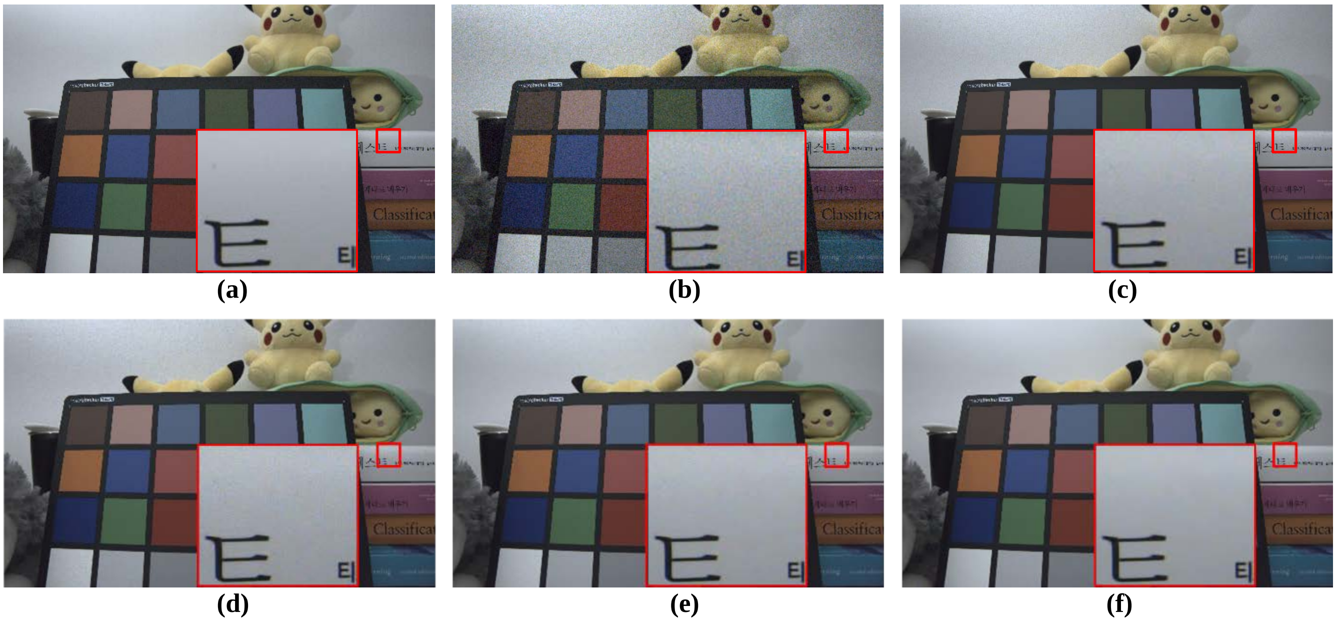


Figure 3. (a) Ground truth image; (b) Noisy image; (c) Global estimation[4] & denoising; (d) Proposed global noise estimation & denoising; (e) Proposed global noise estimation & localized denoising; (f) Proposed localized noise estimation & denoising

Fig 1. (a) shows a Bayer raw image of the color checker. The signal level differs for each of the color patches in the color checker, and consequently has different signal-dependent noise levels. This can be seen from Fig. 1 (b), which shows estimated signal-dependent noise levels for 24 color patches, from top left to bottom right. Global denotes the overall noies level for the entire image. We see that the local noise level highly variates, and thus localized denoising according to local noise levels is required. Conventional noise estimation methods are not appropriate for local, signal-dependent noise estimation. For signal-dependent noise, the noise level differs with signal intensity, and thus noise should be estimated locally.

In this work, a method of signal-dependent noise estimation and denoising that operates on the CFA (color filter array) raw image is proposed and evaluated on a simulated end-to-end imaging pipeline that resembles those of actual imaging devices.

In section 2.1, the proposed noise level estimation on texture domain method is explained. In section 2.2, we explain how the proposed noise level estimation can be applied to different Bayer pattern components and how the scene-dependent noise can be removed. In the experimental results, we evaluate the scene-dependent noise removal performance by using different scene irradiance.

2. Proposed Method

2. 1 Noise estimation on texture domain

Noise estimation is by definition based on separating noise from the image signal. If there is large fluctuation in the signal, it is difficult to distinguish signal from noise. Naturally, noise estimation methods try to find flat or little-varying homogenous regions to estimate the level of noise. One such a method proposes weak textures on which noise is estimated [4].

In a flat image patch, the minimum variance direction of the image should have a very small eigenvalue. If not, this can be attributed to noise. Let us assume an additive noise model $y = x + n$, where y is the noisy image, x is the noise-free image and n is the additive noise. Then, the noise strength can be expressed as

$$\lambda_{min}(\Sigma_y) = \lambda_{min}(\Sigma_x) + \sigma_n^2 \qquad (1)$$

where λ_{min} denotes the minimum eigenvalue, Σ is the covariance matrix, σ_n^2 is the noise variance. Since in a flat patch $\lambda_{min}(\Sigma_x) \rightarrow 0$, the noise variance can be estimated as,

$$\sigma_n^2 = \lambda_{min}(\Sigma_y) \qquad (2)$$

However, because of the signal-dependent noise, the noise level in flat regions is not equal to those in other regions. Signal-dependent noise level differs according to the local signal intensity. Therefore, we propose a localized noise estimation. In particular, when the local region subject to noise estimation is highly deficient of flat object, the noise estimation tends to be very inaccurate. To overcome this problem of sample deficiency, we decompose the image into edge and texture domains [5] which are given by

$$y = y_e + y_t \tag{3}$$

where subscripts *e* and *t* denote edge and texture domains. Using this decomposition method, even when there is large fluctuation in the signal, the texture components (containing noise) can be extracted effectively. Therefore, there is no deficiency of flat patches and signal-dependent noise can be locally estimated on the texture domain.

2. 2 Local and RGB component-wise noise estimation

The raw output of a digital camera is demosaicked to form three color channels. Demosaicking is a process of interpolating missing (mosaicked) color components using the information of other color channels. During demosaicking, noise in each color channel is propagated to other color channels. This causes the formerly independent noise to become correlated, which means its characteristic is complexed and hard to analyze theoretically, e. g. in terms of probability distributions [3]. To avoid such complexity, noise estimation and denoising should take place before the demosaicking process.

Since the CFA (color filter array) raw image is mosaicked, denoising methods that operate on spatial domain cannot be directly applied. Therefore, we aggregate pixels corresponding to different locations in the CFA pattern to obtain what we denote the CFA LR (low resolution) components.

Component-wise noise estimation enables us to estimate signal-dependent noise more accurately. Here, although the structure of CFA LR components may be similar, the intensity of each channel obviously differs. Different scene objects and sensor sensitivities result in highly different intensity levels [3] and this means the noise level in the image is highly spatially variant. Assuming that the illuminant is constant, the signal intensity largely varies with the sensor sensitivity and scene reflectance. Therefore, noise estimation should locally adapt to the imaging scene.

Due to the localized denoising, block boundary effects may occur, and we apply patch overlap to reduce such artifact. After a local image block is processed, the next image block has a 20-pixel overlap with the previously processed block. Overlapped pixels are averaged and their relative weights are given according to the estimated noise. The pixel of the block with lower (estimated) noise is given larger weight.

Once the component-wise denoising is done, the denoised CFA LR components are replaced in their respective locations in the Bayer pattern. Finally, the denoised Bayer CFA raw image is demosaicked to form an enhanced full native resolution image. The whole pipeline is depicted in Fig. 2.

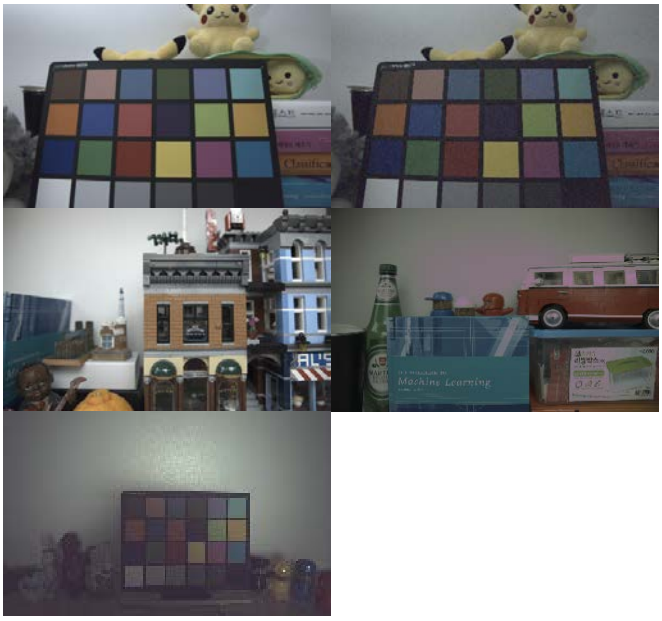


Figure 4. 5 in-door test raw images

Table 1. End-to-end imaging pipeline PSNR.

	Noise estimation + Denoising	PSNR(dB)
Image 1	Global + BM3D	36.57
	Local + BM3D	**37.81**
Image 2	Global + BM3D	35.03
	Local + BM3D	**35.94**
Image 3	Global + BM3D	29.88
	Local + BM3D	**30.51**
Image 4	Global + BM3D	27.35
	Local + BM3D	**27.56**
Image 5	Global + BM3D	29.72
	Local + BM3D	**30.50**

3. Experimental Results

In order to evaluate the proposed noise estimation and denoising methods, we obtained raw images (CR2 format) of diverse scenes using Canon 5D Mark III. We used patch sizes 7x7 and search region size 100x100 for localized noise estimation. The proposed localized noise estimation and denoising is compared to global noise estimation and denoising, using the renowned BM3D [6].

Because there are no actual noise-free ground truth images, we generated pseudo noise-free ground truth images using temporal multi-frame images. We took 500 shots each for three static in-door scenes. The average of 500 shots is used as the pseudo ground-truth image [7].

As in Fig. 2, we apply the proposed denoising scheme in the end-to-end simulated imaging pipeline, as in an actual imaging device. Performance is evaluated at each step of the pipeline as well as after at the end of the pipeline including the white balance, which is the usual domain for quality evaluation. Fig. 3 (a)-(f) show final results of the simulated imaging pipeline; (a) is the mean of 500 shots as the pseudo ground-truth, (b) is the noisy image, (c) is the global noise estimation [2] an denoising result, (d) is the proposed method for global noise estimation and denoising result, (e) is the proposed method for global noise estimation and localized denoising result, (f) is the proposed localized noise estimation and denoising result. Table 1 shows the PSNR results for our test image set. The PSNR and result images show that the localized noise estimation and denoising is superior to global noise estimation and denoising given signal-dependent noise.

4. Conclusion

This work proposed a localized noise estimation and denoising scheme for CFA raw images. The experimental results indicate that the proposed localized noise estimation and denoising deals better with signal-dependent noise. The proposed method was evaluated at each step of the imaging pipeline and indeed turned out to be superior to global noise estimation and denoising at every step.

Acknowledgement

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