Noise Reduction Method for Image Signal Processor Based on Unified Image Sensor Noise Model

Yeul-Min BAEK†a), Student Member and Whoi-Yul KIM†, Nonmember

SUMMARY The noise in digital images acquired by image sensors has complex characteristics due to the variety of noise sources. However, most noise reduction methods assume that an image has additive white Gaussian noise (AWGN) with a constant standard deviation, and thus such methods are not effective for use with image signal processors (ISPs). To efficiently reduce the noise in an ISP, we estimate a unified noise model for an image sensor that can handle shot noise, dark-current noise, and fixed-pattern noise (FPN) together, and then we adaptively reduce the image noise using an adaptive Smallest Unvalue Segment Assimilating Nucleus (SUSAN) filter based on the unified noise model. Since our noise model is affected only by image sensor gain, the parameters for our noise model do not need to be re-configured depending on the contents of image. Therefore, the proposed noise model is suitable for use in an ISP. Our experimental results indicate that the proposed method reduces image sensor noise efficiently.

key words: image signal processor, noise modeling, denoising, image sensor, SUSAN filtering

1. Introduction

Image sensors are widely used not only in digital cameras but also in mobile phones, tablet computers, and vehicles. An ISP is a system on a chip (SoC) that improves image quality by using the output from the image sensor. Noise reduction is a major function in an ISP because all images acquired from an image sensor have noise. Nowadays, small-sized image sensors are preferred for compact imaging devices. However, small-sized image sensors have much noise [1]. Therefore, the need for techniques to reduce image sensor noise in an ISP has been increasing recently.

Many noise reduction methods assume that the noise is AWGN with a constant standard deviation. However, noise from an image sensor is not AWGN, and has some spatial correlation (not white), dependence of intensity (not a constant standard deviation), and a non-Gaussian distribution in the strict sense [2]. Furthermore, in low light conditions, impulsive noise is likely to appear [3]. Therefore, noise reduction methods that assume AWGN are not effective for an ISP.

In addition to noise reduction, an ISP has many other functions, including auto exposure, auto white balance, auto focus, color interpolation, gamma correction, and color correction. Therefore, a noise reduction method in an ISP needs low memory usage and low computational complexity properties.

In this paper, we propose a noise modeling and reduction method for an ISP. To efficiently reduce the image sensor noise in the ISP, we estimate a unified noise model of the image sensor by using an offline process. Then we adaptively reduce the noise using our noise model. Specifically, our unified noise model focuses on dark-current noise, shot noise, and FPN together, and does not need to be re-configured. Therefore, our noise model is accurate over the whole range of intensities, and can be stored in the form of a small look-up table. The proposed noise reduction method performs adaptive SUSAN filtering based on our noise model. The proposed method is simple and can also reduce impulsive noise in low light conditions.

The paper is organized as follows. We review related research in Sect. 2. In Sect. 3, we describe how to estimate the unified noise model. In Sect. 4, we describe how to reduce the image noise in an ISP. We show the experimental results in terms of the properties of our noise model and the noise reduction performance in Sects. 5 and 6, respectively. Finally, concluding remarks are provided in Sect. 7.

2. Related Work

Many noise reduction methods have been proposed using various techniques, such as wavelet [4], [5], total variation [6], [7], and bilateral filtering [8]–[10]. In these methods, it is assumed that the noise is AWGN with a constant standard deviation for varying intensity values. Thus, these methods are not efficient at removing image sensor noise, and the parameters must be adjusted manually [11]. The study of noise modeling has been relatively limited. In [12], Hwang et al. modeled shot noise, the dominant noise of an image sensor, as a Skellam distribution from a single image. In general, shot noise is often characterized by the Poisson distribution. However, in many noise estimation methods, shot noise is modeled as a Gaussian distribution based on the assumption that the photon arrival rate is high. However, when the intensity value of an image is low, treating the shot noise as a Gaussian distribution may not be appropriate. The Skellam distribution, or a discrete probability distribution of the difference between two random variables having Poisson distributions, was proposed by Hwang et al. for use as a shot noise model for the intensity difference. However, as noted in [3], [13], [14], since noise characteristics tend to be distorted due to the post-processing of the camera pipeline, such as demosaicing, gamma correction, and white balancing, it was difficult to find a proper noise...
model in terms of the Intensity-Skellam line. To avoid such distortions of the noise characteristics, Liu et al. suggested a noise model called the noise level function based on the piecewise smooth image prior model [11]. They built the space of noise level functions and used the Bayesian MAP inference to infer noise level function from a single image. However, in their method, the parameters for the model had to be re-estimated for each input image. Therefore, the computational complexity of their method was too high to be used for an ISP. In [3], [13], [14], they estimated the parameters for the noise model in the Bayer domain to avoid distortion of the noise characteristics, and then adaptively determined the filter coefficients using their model. However, since they modeled only the shot noise, those methods become imprecise when the intensity is high.

3. Unified Noise Modeling

In this section, we describe our model of image sensor noise. In our previous approach [22], we modeled dark-current noise, shot noise, and FPN together. However, the approach needs too many images for dark-current noise modeling and has high computational complexity due to iterative square root and exponential operations for reducing image noise. Also, it is hard to reduce impulsive noise. The proposed method has an improved noise model from our previous approach and a novel noise reduction filter based on our noise model. In comparison with our previous approach, the proposed method needs only two images for dark-current noise modeling. The proposed method does not need iterative square root and exponential operations and thus can be applied to an ISP. Also, the proposed method can reduce impulsive noise in low light conditions.

As observed in [15], there are five main noise sources, FPN, dark-current noise, shot noise, amplifier noise, and quantization noise. We do not consider amplifier noise and quantization noise, because the levels of these two types of noise are low and can be considerably reduced by appropriate design. Most noise modeling methods deal only with shot noise. However, when the image intensity is high or low, fixed-pattern or dark-current noise becomes a dominant noise source, respectively [13]. Therefore, in order to build a precise noise model of the image sensor, we propose a unified noise model that can handle dark-current noise, shot noise, and FPN simultaneously.

3.1 Noise Modeling in the Bayer Domain

Noise modeling means the process of modeling the noise as a function of the image intensity. Noise level samples are collected from homogeneous patches of an input image. Figure 1 shows such noise samples in our experiment described in [12], in which a line equation was used as the noise model. However, Fig. 1 shows that it is difficult to identify a linear relationship between noise samples.

The ISP post-processing causes this non-linearity [3], [13]. Figure 2 shows a typical pipeline of an imaging device. As shown in Fig. 2, Image sensor output values with Bayer filter mosaic, before demosaicing and processing, lie in a linear space called the Bayer domain. Image domain refers to the final intensity values which are generated by a series of post-processing steps after the Bayer domain. In Fig. 2, the camera response function (CRF), including gamma correction and white balance, shows that the noise level bears non-linear characteristics. In addition, the demosaicing process for the Bayer pattern causes the noise to be correlated between color channels, as well as spatial correlation [3], [13]. Therefore, it is difficult to build an accurate noise model from an image in the image domain. To build an accurate yet simple noise model, we build our noise model in the Bayer domain.

The image from an imaging device can be expressed as

\[ I = f(Z) \]  \hspace{1cm} (1)

\[ Z = L + n_{\text{unified}} \]  \hspace{1cm} (2)

Here, \( L \) is the noiseless irradiance, \( Z \) and \( I \) are the intensities in the Bayer domain and the image domain, respectively.

![Fig. 1](image1.png)  \hspace{1cm} (a) R channel  \hspace{1cm} (b) G channel  \hspace{1cm} (c) B channel

Fig. 1 Non-linearity characteristic of noise in the image domain.

![Fig. 2](image2.png)  \hspace{1cm} Pipeline of imaging device.
and \( n_{\text{unified}} \) is the noise estimated by our unified noise model. \( f \) is a CRF that transforms the intensity in the Bayer domain into the intensity in the image domain. In general, photon arrival obeys a Poisson distribution. However, unless the photon arrival rate is very low, the Poisson distribution can be approximated by the Gaussian distribution [16]. Therefore, we can assume that the unified noise model has zero mean additive Gaussian noise given by

\[
n_{\text{unified}}: N(0, \sigma_{\text{unified}}^2) \left( \sigma_D^2(L, \sigma_F^2(L), d_{\text{offset}}) \right)
\]

where \( \sigma_D^2(L) \) is the variance of the dark-current noise as a function of the exposure time \( t \), \( \sigma_F^2(L) \) is the variance of the shot noise as a function of the intensity \( L \), and \( d_{\text{offset}} \) denotes the offset intensity caused by dark-current.

In the Bayer domain, there is no correlation between the color channels. Therefore, our noise model is independently estimated from each color channel.

### 3.2 Dark-Current Noise Modeling

Ideally, the output signal from an image sensor should be zero when there is no incident light on the image sensor. However, the actual output signal from the image sensor in the absence of incident light is not zero, but some offset intensity with dark-current noise because of dark-current electrons.

To model the dark-current noise, we acquire dark-frame images with respect to exposure time. The dark-frame images can be acquired in a darkroom using a camera with a closed lens cap.

Since dark-current noise is spatially random, the global mean intensity can be regarded as the noiseless intensity \( L_D \) caused by dark-current electrons. The global mean intensity from each dark-frame image of size \( M \times N \) is computed by

\[
L_D = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} Z_D(x,y)
\]

where \( Z_D(x,y) \) denotes the intensity observed at the pixel position \( (x, y) \) in the Bayer domain.

As shown in Fig. 3 (a), the global mean intensity values of the dark-frame images are almost the same (\( \sigma = 0.1 \)), even though the exposure time has changed. Therefore, the offset intensity caused by dark-current \( d_{\text{offset}} \) is computed by averaging \( K \) different dark frame images according to the exposure time:

\[
d_{\text{offset}} = \frac{1}{K} \sum_{i=1}^{K} L_{D,i}
\]

Since dark-frame images are homogeneous, the standard deviation of the dark-current noise \( \sigma_D \) is computed as a global standard deviation given by:

\[
\sigma_D = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (Z_D(x,y) - L_D)^2}
\]

In Fig. 3 (b), the standard deviation of the dark-current noise \( \sigma_D \) is plotted against the exposure time, \( t \). As shown in Fig. 3 (b), the standard deviation of the dark-current noise has a linear relationship with the exposure time. Therefore, we estimate the dark-current noise \( \sigma_D(t) \) as a linear function of the exposure time as shown:

\[
\sigma_D(t) = a_0 + a_1 t
\]

In Eq. (7), the coefficients \( a_0 \) and \( a_1 \) are simultaneously calculated by fitting a line to a set of paired observation samples: \( (t_1, \sigma_{D,1}), (t_2, \sigma_{D,2}), \ldots, (t_n, \sigma_{D,n}) \) based on the least square regression.

### 3.3 Shot Noise Modeling

Shot noise or photon shot noise is caused by the inherent natural variation of incident photon flux. Since shot noise is spatially random in the Bayer domain, we can estimate meaningful statistics using homogeneous image patches. The mean and variance of each homogenous patch are considered to have noiseless intensity \( L_S \) and a relative shot noise variance \( \sigma_F^2 \).

To estimate the shot noise, we acquire a single image of a color checker as shown in Fig. 4 (a). Then we extract the homogeneous color patches and compute the mean and variance from each patch as

![Fig. 3](image1)  
(a) Dark-current noise model. (a) is the intensity value of dark-frame images as a function of exposure time, and (b) is the noise standard deviation of dark-frame images as a function of exposure time.  
![Fig. 4](image2)  
(a) Shot noise modeling. (a) is a GretagMacbeth™ color checker chart for modeling shot noise, and (b) is the shot noise model obtained by fitting a line to the shot noise samples marked “O” (\( L_{S,n}, \sigma_{F,n}^2 \), (ISO 800, R channel).
\[
L_S = \frac{1}{k} \sum_{(x,y) \in P} Z_S(x,y)
\]  
(8)

\[
\sigma^2_S = \frac{1}{k} \sum_{(x,y) \in P} (Z_S(x,y) - L_S)^2
\]  
(9)

where \( P \) is the set of pixels in the patch, and \( k \) is the number of pixels in the patch.

Figure 4(b) shows that the variance of the shot noise has a linear relationship with the mean intensity in the Bayer domain. Therefore, we again apply the line fitting strategy using the least square regression method. We estimate the shot noise model as a linear function of the intensity in the Bayer domain by

\[
\sigma^2_S(L) = b_0 + b_1 L
\]  
(10)

When a set of observation samples: \( (L_{S,1}, \sigma^2_{S,1}), (L_{S,2}, \sigma^2_{S,2}), \ldots, (L_{S,n}, \sigma^2_{S,n}) \) is given by Eq. (8) and Eq. (9), the coefficients \( b_0 \) and \( b_1 \) are computed by the least square regression.

### 3.4 Fixed-Pattern Noise Modeling

FPN is caused by a difference in pixel response. Therefore, FPN becomes a dominant noise source when the intensity is high.

According to the noise measurement method specified by the ISO 15739 standard [17], the FPN standard deviation for the given intensity is obtained by acquiring a sequence of ISO 15739 test chart images.

When a sequence of images of the ISO 15739 test chart: \( L_{F,1}(x,y), L_{F,2}(x,y), \ldots, L_{F,n}(x,y) \) is acquired, the average image is

\[
L_{\text{ave}}(x,y) = \frac{1}{n} \sum_{i=1}^{n} L_{F,i}(x,y)
\]  
(11)

and the \( i \)th difference image is given by

\[
L_{\text{diff},i}(x,y) = |L_{F,i}(x,y) - L_{\text{ave}}(x,y)|
\]  
(12)

According to the ISO 15739 standard, the given intensity \( L_{\text{sat}} \) is computed by

\[
L_{\text{sat}} = \frac{1}{k} \sum_{(x,y) \in P} L_{\text{ave}}(x,y)
\]  
(13)

where \( P \) is the center homogeneous patch of the ISO 15739 test chart as shown in Fig. 5, and \( k \) is the number of pixels in the patch. Then the standard deviation of FPN \( \sigma_{fp} \) with the related intensity \( L_{\text{sat}} \) is computed by

\[
\sigma_{fp} = \sqrt{\frac{\sigma^2_{ave} - \frac{1}{n-1} \sigma^2_{\text{diff}}}{n}}
\]  
(14)

In Eq. (14), \( \sigma^2_{ave} \) is the variance of the average image \( L_{\text{ave}} \) as follows:

\[
\sigma^2_{ave} = \frac{1}{k} \sum_{(x,y) \in P} (L_{\text{ave}}(x,y) - L_{\text{sat}})^2
\]  
(15)

and \( \sigma^2_{\text{diff}} \) is computed by:

\[
\sigma^2_{\text{diff}} = \frac{1}{n} \sum_{i=1}^{n} \sigma^2_{\text{diff},i}
\]  
(16)

where \( \sigma^2_{\text{diff},i} \) is the variance of \( i \)th difference image \( L_{\text{diff},i} \) computed by Eq. (17) and Eq. (18).

\[
\mu_{\text{diff},i} = \frac{1}{k} \sum_{(x,y) \in P} L_{\text{diff},i}(x,y)
\]  
(17)

\[
\sigma^2_{\text{diff},i} = \frac{1}{k} \sum_{(x,y) \in P} (L_{\text{diff},i}(x,y) - \mu_{\text{diff},i})^2
\]  
(18)

Since FPN is caused by differences in pixel responses, we investigated five different randomly selected pixel responses in our experiment. As shown in Fig. 6(a), the response of different pixels increased linearly. Thus we assume that the FPN standard deviation increases linearly with respect to the intensity, and we use a line equation that passes through the origin and \( (L_{\text{sat}}, \sigma_{fp}) \) as the FPN model.

The FPN model, \( \sigma_F(L) \) is computed by

\[
\sigma_F(L) = c_0 L
\]  
(19)

\[
c_0 = \frac{\sigma_{fp}}{L_{\text{sat}}}
\]  
(20)

### 3.5 Unified Noise Terms

In this section, we unify dark-current noise, shot noise, and FPN. The standard deviation of the unified noise model as a function of the intensity and exposure time is given by

\[
\sigma_{\text{unifed}}(L, t) = \begin{cases} 
\sigma_{fp}(t) & \text{if } (L \leq d_{\text{offset}}) \\
\sqrt{\sigma^2_S(L) + \sigma^2_F(L)} & \text{else}
\end{cases}
\]  
(21)

In Eq. (21), when the intensity is lower than \( d_{\text{offset}} \), the image
is only corrupted by the dark-current noise. When the intensity is higher than \( d_{\text{offset}} \), the unified noise should consist of dark-current noise, shot noise, and FPN. However, since shot noise is associated with the portion of dark-current noise [18], only the shot noise and FPN terms are added when the intensity is higher than \( d_{\text{offset}} \). In most cases, \( L \) is bigger than \( d_{\text{offset}} \) and \( \sigma_D(t) \) has a small variance. Therefore, our unified noise model can be approximated by

\[
\begin{align*}
\text{if } (L \leq d_{\text{offset}}) & : \quad \sigma_{\text{unified}}(L) = \frac{(\sigma_D(t_{\text{max}})+\sigma_D(t_{\text{min}}))}{2} \\
\text{else} & : \quad \sigma_{\text{unified}}(L) = \sqrt{\sigma^2_S(L) + \sigma^2_D(L)}
\end{align*}
\]

(22)

where the exposure times \( t_{\text{max}} \) and \( t_{\text{min}} \) can be determined by the specifications of the target imaging device.

4. Noise Reduction Using the Unified Noise Model

Since our unified noise model is built in the Bayer domain, the proposed noise reduction method should be performed in the Bayer domain. Our unified noise model can be combined with various noise reduction filter techniques. The proposed noise reduction method uses the SUSAN filtering [19] in the Bayer domain.

4.1 Adaptive SUSAN Filter

SUSAN filtering is an edge-preserving smoothing algorithm, similar to the famous bilateral filtering method. SUSAN filtering only smooths neighbors that have a similar intensity as that of a center pixel. The difference is that the SUSAN filter does not use a center pixel for weighted-averaging.

In this section, we present an adaptive SUSAN filter using the unified noise model. The denoised result image is computed by

\[
L'(x,y) = \frac{\sum_{(i,j)\neq 0} Z(x+i,y+j)w_d(x,y,i,j)w_r(x,y,i,j)}{\sum_{(i,j)\neq 0} w_d(x,y,i,j)w_r(x,y,i,j)}
\]

(23)

where \( Z(x,y) \) is the input intensity and \( L'(x,y) \) is the denoised intensity at the pixel position \( (x,y) \). \( \Omega \) is the neighborhood set of the Bayer domain. \( w_D \) is the domain filter computed based on the spatial distance as

\[
w_d(x,y,i,j) = \exp\left(-\frac{1}{2}\frac{||((x,y)-(x+i,y+j))||^2}{\sigma_d}\right)
\]

(24)

where \( \sigma_d \) controls the scale of the spatial smoothing for noise reduction. \( w_r \) is the range filter computed based on the intensity difference as

\[
w_r(x,y,i,j) = \exp\left(-\frac{1}{2}\frac{||Z(x,y)-Z(x+i,y+j)||^2}{r}\right)
\]

(25)

where \( r \) is the intensity threshold for preserving edges. In other words, the range weight can be regarded as the probability of whether or not the intensity difference is caused by noise.

\[
r = \sigma_{\text{unified}}(Z(x,y))
\]

(26)

where \( \sigma_{\text{unified}} \) is our noise model in Eq. (21) or Eq. (22).

Our noise model is a function of the noiseless intensity \( L \). However, the observation intensity is corrupted by noise as expressed in Eq. (2), and can be corrupted by impulsive noise in low light conditions from a CMOS image sensor. Therefore, if we use the center pixel in Eq. (23), it is harder to reduce noise effectively, as the observation intensity is more strongly corrupted with noise. This is the reason that we use SUSAN filtering instead of bilateral filtering.

4.2 Implementation

To store our unified noise model in an ISP, we need memory space for only 6 parameters: \( a_0, a_1, b_0, b_1, c_0 \), and \( d_{\text{offset}} \). However, we construct a two-dimensional look-up table by sampling our noise model and the adaptive SUSAN filter. This look-up table makes the square root and exponential operations unnecessary. Therefore, we can reduce the computational complexity in an ISP.

As expressed in Eq. (25) and Eq. (26), the range filter weight is computed by the Gaussian distribution with the standard deviation from the unified noise model. Therefore, as shown in Fig. 7 (a), if we sample the noise model and its corresponding Gaussian distribution, we can build the look-up table for the adaptive SUSAN filtering. First, as shown in Fig. 7 (b), we make a 2D surface by using the unified noise model and its corresponding Gaussian distribution. Then we build the look-up table by 2D sampling. If an adaptive sampling technique is used, a more effective look-up table can be built. In this paper, we just divided the 2D surface along the \( Z(x,y) \) axis into 256 equal parts, and the \( ||Z(x,y)-Z(x+i,y+j)|| \) axis into 4 parts: \( 0, 2r, 2r, \) and \( 3r \). Thus, only 256 \( \times \) 4 samples were extracted for the look-up table, and we use bilinear interpolation for computing the range filter weight according to the arbitrary input intensity. If we allocate 32 bit

![Fig. 7 Sampling of the unified noise model. (a) Range filter weight from unified noise model, (b) 2D LUT.](image-url)
memory for one sample, our noise model for the adaptive SUSAN filter can be stored in just 4 Kbytes per color channel.

5. Experimental Results on Noise Model

To verify our noise model, we performed experiments on both real and synthetic noise images, and tested our noise model behavior depending on the camera setting. Real images for the experiment were acquired by a Canon™ EOS Digital Kiss X camera and we followed the environment condition specified ISO 15739, such as the light source, diffuser, reflector, temperature, humidity, white balance, test chart. Since our noise modeling method uses Bayer domain images, we acquired raw images and used the software dcraw to extract Bayer domain images from the raw image files. dcraw is an open source program that is able to read numerous raw image formats [20]. As shown in Fig. 8, the Bayer pattern of the used camera is a universal RGGB pattern. Thus, our noise reduction filter kernel was designed corresponding to the Bayer pattern.

The camera used supports five ISO settings: ISO 100, 200, 400, 800, and 1600. However, the images acquired from ISO 100 and ISO 200 have very little noise. Therefore, for convenience, we built three unified noise models using images acquired at ISO 400, 800, and 1600. We used the simple version of the noise model as in Eq. (22). Thus, only two images were used for the dark-current noise model. For the shot noise model, we used the given homogeneous patches in the GretagMacbeth™ color checker chart. Thus, we used 24 homogeneous patches. For the FPN model, we used eight images as recommended in the ISO 15739 standard.

The camera settings used are as follows. The exposure time $t_{\min}$ was $1/4000$ sec, $t_{\max}$ was 30 sec, and the aperture F11 was used for the dark-current noise model. F11 and $1/13$ sec were used for both the shot noise model and the FPN model. The same camera setting was used at each ISO setting. The information regarding the camera settings used is actually meaningless, because arbitrary camera settings can be used. We will discuss this factor in the next section.

5.1 Robustness of the Unified Noise Model

We ran some experiments to determine how our noise model works due to changes in the camera parameter settings such as the aperture, shutter speed, and sensitivity setting of the image sensor (ISO setting). At first, we fixed the ISO setting and changed the aperture and shutter speed. The results are shown in Fig. 9 and Table 1.

As Fig. 9 indicates, although the aperture and shutter speed changed, our noise model exhibited very little variation. Table 1 shows the variance values among our noise models with different aperture and shutter speed settings. In Table 1, the intensity range is normalized between 0 and 1. Since the variance is small as shown in Table 1, the PSNR values of noise reduction results of Fig. 14 (a) are almost the same with our noise models which were created from different aperture and shutter speed as shown in Table 2.

In the same manner, the results of our noise model with different ISO settings are shown in Fig. 10. As Fig. 10 indicates, only the sensitivity setting of the image sensor affected our noise model.

These two properties indicate that our noise model does not need to be reconfigured for different input images if it is...
used according to each ISO setting. Therefore, our compact noise model is applicable to an ISP in the form of a look-up table.

5.2 Comparison with Ground-Truth Noise Samples

To collect ground-truth noise samples as shown in Fig. 11, we acquired 52 color checker images with various exposure times (1/4000 sec ~ 30 sec) and computed the mean intensity and standard deviation of 24 patches from each color checker image. Then we compared our noise model with the ground-truth noise samples. The result is shown in Fig. 11. As anticipated, our noise model estimated the upper-boundary of the ground-truth noise samples steadily. The figure shows that the ground-truth noise samples are scattered when the intensity is high. This is caused by the FPN, as the upper-boundary noise samples are corrupted by the FPN. On the other hand, the lower boundary noise samples, which have only shot noise, were bounded by the proposed shot noise model (dashed line). Since our noise model focuses dark-current noise, shot noise, and FPN together, the precise noise level can be estimated without under-estimation problem.

5.3 Comparison with a Synthetic Noise Model

To generate the synthetic noise image as shown in Fig. 12, we specified the parameters \((a_0, a_1, b_0, b_1, c_0, d_{\text{offset}})\) for our unified noise model and generated the synthetic noise images as specified in our noise model. Since dark-current noise and shot noise are Gaussian random noise types, we generated these two Gaussian noises with the standard deviation according to the intensity. In numerous cases, the FPN shows a line-wise pattern because of a manufacturing problem. Therefore, we multiplied the constant gain \(\alpha\) by every second column from the synthetic noise image to generate the FPN. The constant gain alpha can be computed by

\[
\alpha = 2c_0 + 1
\]

because the FPN of a synthetic noise image should follow the specified FPN model as shown:

\[
\sqrt{\frac{1}{2}(L - \frac{L + aL}{2})^2 + \frac{1}{2}(aL - \frac{L + aL}{2})^2} = c_0L
\]

To estimate the FPN model from synthetic noise images
as mentioned in Sect. 3, we generated eight synthetic noise images.

The results, as shown in Fig. 13 and Table 3, show that the estimated unified noise model from the synthetic noise images is very close to the pre-specified synthetic unified noise model. In Table 3, the intensity range is normalized from 0 to 1.

6. Experimental Results on Noise Reduction

To verify our noise reduction method, we compared our noise reduction method with the bilateral filter [8], the noise reduction filter in Photoshop™ CS4, CMOSNR (CMOS Noise Reduction) filter [3] and MTV (Modified Total Variation) filter [7]. As mentioned in Sect. 5, all experimental images are acquired by a Canon™ EOS Digital Kiss X camera following the environment condition specified by ISO 15739 and dcraw is used to extract the Bayer domain images from the camera.

Our noise model and reduction filter are defined in the Bayer domain. Therefore, we perform demosaicing and the CRF process to get the denoised results in the image domain for display. We simply used bilinear interpolation as demosaicing and the estimated CRF of the camera following the method described in [21].

The window size of the adaptive SUSAN filter was 7×7 for low computational complexity in an ISP, and the $\sigma_d$ in Eq. (24) was 3. For a fair comparison, the same filter size was used for the compared methods, and all other parameters of the compared methods were set according to the best performance results even though the parameters of our method are fixed.

We use the PSNR value as the measure to compare the noise reduction performance. We need the noise-free image as the ground-truth for computing the PSNR. However, the noise-free image could not be acquired from any image acquisition devices. Therefore, we acquired 100 images toward a static scene and estimated the noise-free image by averaging a sequence of 100 images, on the assumption that the mean of the noise is zero. The PSNR results are shown in Table 4. As Table 4 indicates, the PSNR of the proposed method is higher than those of other conventional methods.

Figure 14 shows result images used for the PSNR evaluation. In Fig. 15, we use a one dimensional image profile to show the performance with respect to edge preservation and noise reduction. As Fig. 14 and Fig. 15 indicate, our method shows better performance than conventional methods in the sense that edges are preserved and flat regions are well smoothed. Also, the proposed method is more effective to reduce the impulsive noise in dark region. The PSNR values of Photoshop™ CS4 and MTV are lower than the original image at ISO 400. The original image at ISO

Table 4: The PSNR of experimental results.

| Method      | ISO 400 | ISO 800 | ISO 1600 | Average |
|-------------|---------|---------|----------|---------|
| Original    | 40.236  | 36.049  | 32.603   | 36.296  |
| Bilateral   | 42.345  | 39.863  | 35.982   | 39.397  |
| Photoshop™ CS4 | 35.691  | 36.479  | 34.974   | 35.715  |
| CMOSNR      | 42.750  | 39.747  | 36.155   | 39.551  |
| MTV         | 36.494  | 37.053  | 35.829   | 36.459  |
| Proposed    | 43.283  | 40.268  | 37.238   | 40.296  |

Fig. 14  Result images for PSNR evaluation. (a) input noisy image (1400×1540, ISO1600, f11, 1/13 s), (b) cropped image from (a) (indicated by a white box in (a)), (c) bilateral filter, (d) Photoshop CS4, (e) CMOSNR, (f) MTV, (g) proposed.
400 has little noise. However, those two methods showed blurry result images due to over-denoising. It is considered that the methods do not reflect the noise characteristics because of their AWGN with a constant standard deviation assumption. Since the FPN is not temporally random, our estimated noise-free image still includes FPN. Therefore, our PSNR evaluation is not strictly accurate. The evaluation of real noise images is outside of the scope of this study. Nevertheless, our PSNR results are worth considering, because FPN is dominant only when the intensity is high. In addition to the PSNR evaluation, we have conducted experiment on various snapshot images as shown in Fig. 16. As the figure indicates, our method efficiently reduced image noise and preserved details regardless of the scene content.

7. Conclusion

We propose a noise modeling and reduction algorithm for ISPs. To efficiently reduce the image sensor noise, we estimate the unified noise model of the image sensor, and then reduce the image sensor noise using an adaptive SUSAN filter based on our noise model.

Our noise model incorporates dark-current noise, shot noise, and FPN. Our experimental results show that our
Noise model was affected only by the image sensor gain (ISO setting). This means that our noise model does not need to be reconfigured for different images and is suited for ISPs in consumer imaging devices. We showed that our noise model estimates image sensor noise accurately by comparing the results with ground-truth-noise samples and a synthetic noise model. In addition, the use of our adaptive SUSAN filter with the unified noise model is simple and can be stored in very little memory space. In the experimental results on noise reduction, our method shows better noise reduction performance than conventional noise reduction methods.

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Yeul-Min Baek received B.S and M.S degrees in electronics computer engineering in Hanyang University, Seoul, Korea, in 2005 and 2007, respectively. He is now a doctoral candidate in the Department of Electronics Computer Engineering at Hanyang University. His research interests include image enhancement, object detection, and computer vision.

Whoi-Yul Kim received the Ph.D. degree in Electronics Engineering from Purdue University, W.L., IN, USA in 1989. From 1989 to 1994, He was with the Erick Johanson School of Engineering and Computer Science at the University of Texas at Dallas. He joined Hanyang University in 1994 where he is now a professor in the Department of Electronics and Computer Engineering. His research interests include visual surveillance, face tracking and identification, motion analysis, face recognition and MPEG-7 applications, where he contributed to the development of the MPEG-7 visual descriptors.