CMOS Image Sensor Noise Reduction Method for Image Signal Processor in Digital Cameras and Camera Phones

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ABSTRACT

Digital images captured from CMOS image sensors suffer Gaussian noise and impulsive noise. To efficiently reduce the noise in Image Signal Processor (ISP), we analyze noise feature for imaging pipeline of ISP where noise reduction algorithm is performed. The Gaussian noise reduction and impulsive noise reduction method are proposed for proper ISP implementation in Bayer domain. The proposed method takes advantage of the analyzed noise feature to calculate noise reduction filter coefficients. Thus, noise is adaptively reduced according to the scene environment. Since noise is amplified and characteristic of noise varies while the image sensor signal undergoes several image processing steps, it is better to remove noise in earlier stage on imaging pipeline of ISP. Thus, noise reduction is carried out in Bayer domain on imaging pipeline of ISP. The method is tested on imaging pipeline of ISP and images captured from Samsung 2M CMOS image sensor test module. The experimental results show that the proposed method removes noise while effectively preserves edges.

Keywords: CMOS image sensor, noise, image denoising, digital camera, camera phone

1. INTRODUCTION

Digital imaging devices such as digital cameras or camera phones on the market have been rapidly growing. The portion of CMOS image sensor on the market is becoming larger because of its advantages such as high integration, low price, low power consumption etc. However, the quality of images captured from CMOS image sensor is not satisfactory, especially if images are taken in low light condition due to high noise and signal amplification. Unfortunately, Additive White Gaussian Noise (AWGN) model with constant standard deviation does not hold for images captured from imaging devices such as digital cameras and camera phones[1]. Furthermore, in low light condition, impulsive noises are likely to appear. Thus, noise model and noise reduction algorithm, which are characterized for noise in Image Signal Processor (ISP), are required.

Since AWGN model does not hold, we characterize noise in imaging pipeline of ISP by experiments. In the previous research[1], it is investigated that the noise standard deviation is related to signal intensity. Because images are captured after the Auto Exposure (AE) block that controls the signal amplification by changing Auto Gain Control (AGC), the noise standard deviation is affected by AGC. We verify these relationships by experiments and the characterized noise model is applied for noise reduction algorithm of ISP.

Since noise is amplified and characteristic of noise varies while the image sensor signal undergoes several image processing steps, it is better to remove noise in earlier stage on imaging pipeline of ISP. Thus, the proposed noise reduction method is designed for Bayer domain to efficiently reduce noise. Typical imaging pipeline and noise reduction block is demonstrated on figure 1.

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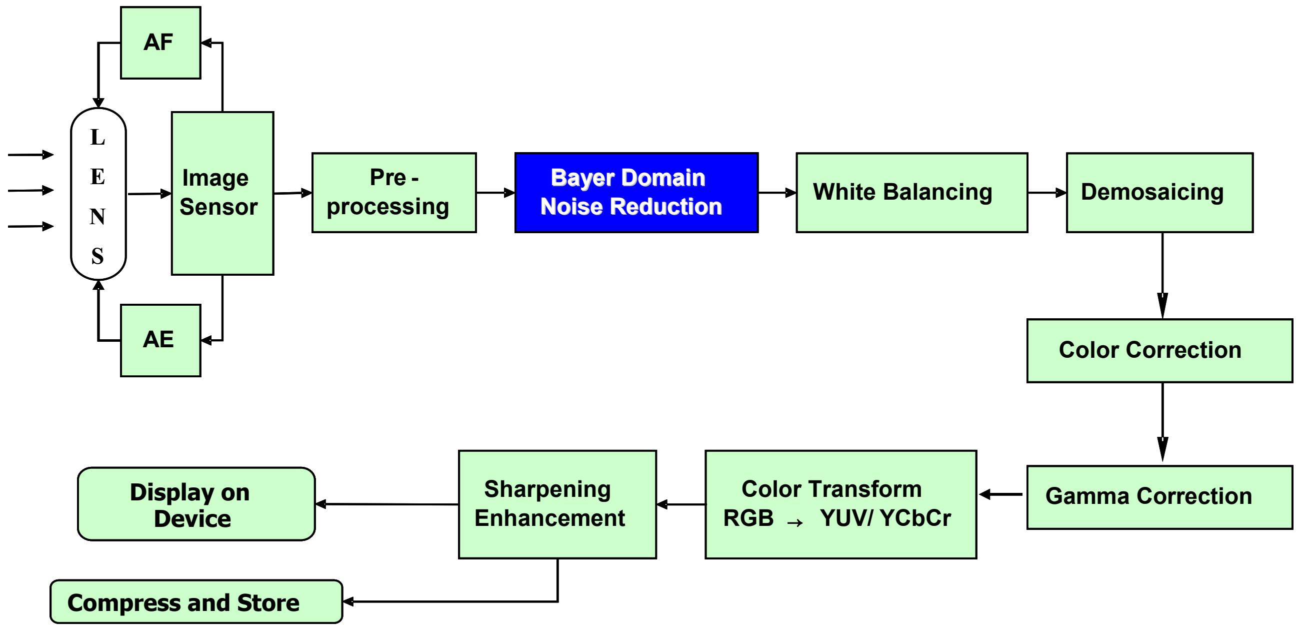


Figure 1. Typical imaging pipeline and noise reduction blocks

The characterization of noise in Samsung 2M CMOS image sensor test module for Bayer domain noise reduction is presented in Section 2. The proposed noise reduction method is developed in Section 3. Section 4 is devoted to demonstration and discussion of experimental results. Finally, concluding remarks are provided in Section 5.

2. ANALYSIS OF NOISE FEATURE FOR BAYER DOMAIN NOISE REDUCTION

CMOS image sensor noise can be classified into fixed-pattern noise (FPN) and temporal random noise. FPN generally has the same spatial location characteristics and statistics from picture to picture. One way to remove FPN is that you find and store the noise value, and subtract the noise value from your picture[2]. Thus, FPN is relatively easy to remove. Temporal random noise is also called time-varying noise. Characteristic of this type of noise deviates from pixel to pixel and from scene environment to scene environment. This type of noise is generally more difficult to remove.

While investigating the source of noise is beyond the scope of this paper, major source of temporal random noise is known as photon shot noise, readout noise etc. In general, photon arrival obeys Poisson distribution. However, when photon arrival rate is high, Poisson distribution can be approximated to Gaussian distribution[3]. We independently verify this by experiments. Luminance value distribution of noisy image patch is shown in figure 2. The image patch is taken from Samsung 2M CMOS image sensor test module. As we can see, it is reasonable to say that the histogram is similar to Gaussian distribution.

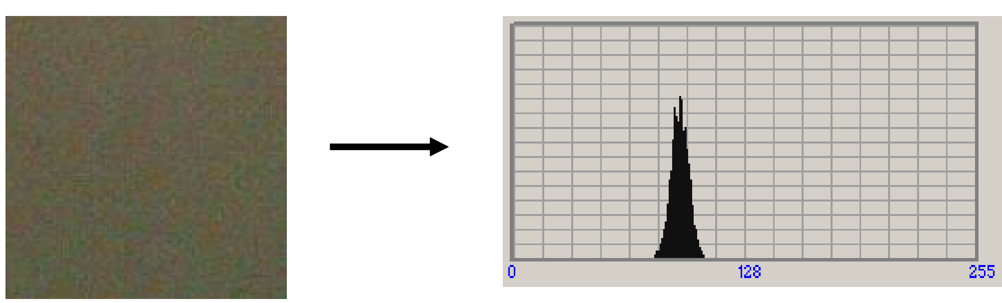


Figure 2. Noisy image patch and histogram

As it is mentioned in Section 1, the standard deviation of temporal noise is related to signal intensity. In order for the noise reduction method to be effective, it is important to apply the noise characteristics to the noise reduction method. We measure the noise standard deviation against the signal intensity by using Kodak gray scale chart. Kodak gray scale chart is shown in figure 3.

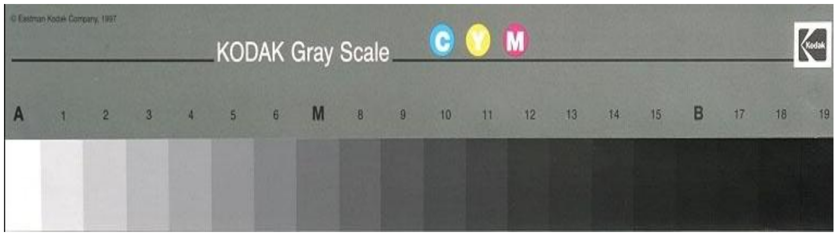


Figure 3. Kodak gray scale chart

In figure 4, the standard deviation of temporal random noise is plotted against the signal intensity for each RGB channel respectively. The line in the plot is averaged and interpolated data from several measured points. The sudden drop around high intensity value is due to saturation error.

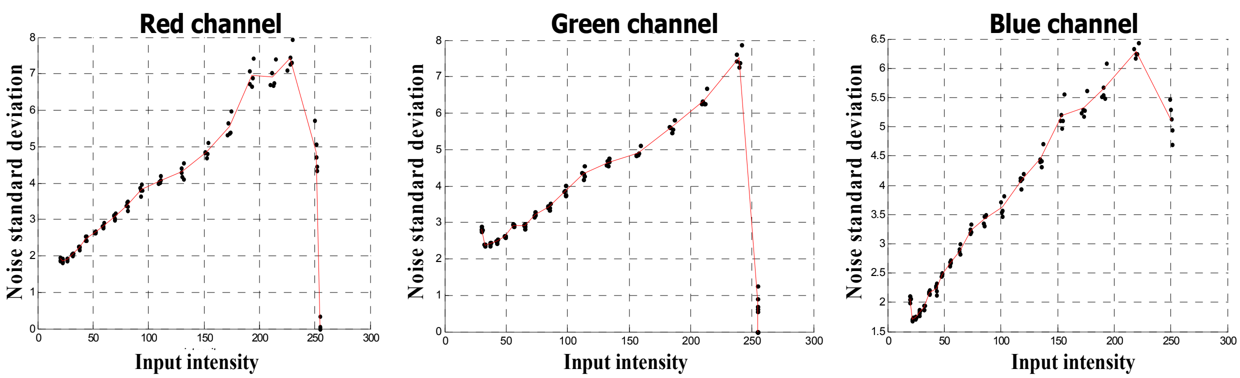


Figure 4. Noise standard deviation against the signal intensity for red, green and blue channels

In digital cameras, the Auto Gain Control (AGC) circuit serves as push and pull processing in film cameras. As the AGC is increased, the standard deviation of noise increases. One can reduce AGC to make higher quality images. However, for low light situations or for very fast subjects, reducing AGC is unacceptable because a longer exposure time is required. The Auto Exposure (AE) control block of ISP determines an optimal AGC value and exposure time for scene environment. As we can see in figure 1, since the Bayer domain noise reduction is performed after the AE control block, relationship between AGC value and standard deviation of noise has to be considered. In figure 5, the relationship between AGC value and standard deviation of noise is plotted for each RGB channel respectively. As we can see in the figure, the AGC value amplifies the standard deviation of noise. The standard deviation of noise in the figure is normalized to be used for *noise level calculator* in noise reduction method. Again, the sudden drop around high AGC value is due to saturation error.

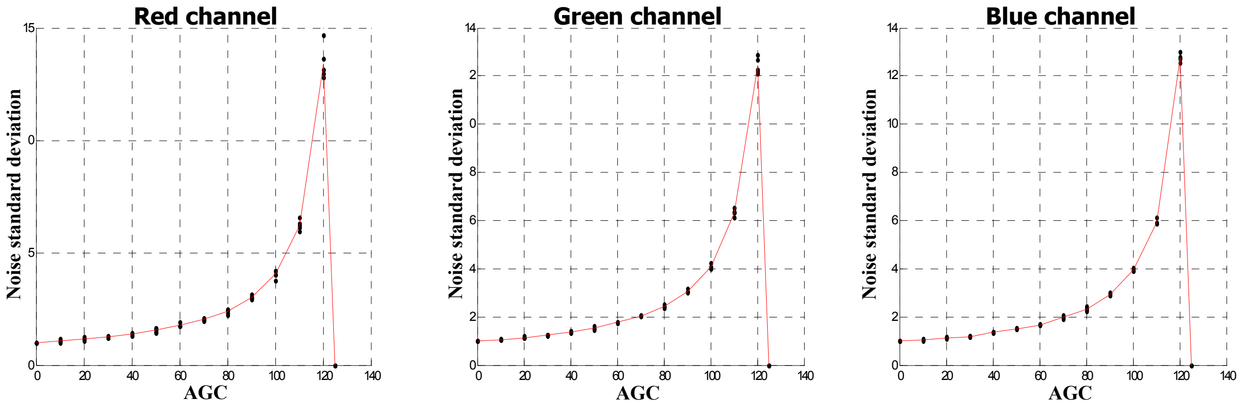


Figure 5. Noise standard deviation against the AGC value for red, green and blue channels

In low light conditions, the exposure tends to be long and this can be one of reasons that impulsive noises are likely to appear. Thus, noise reduction method is proposed in the next section, which is capable of removing Gaussian noise and impulsive noises by using the same filtering kernel.

3. NOISE REDUCTION METHOD

The proposed signal flow of noise reduction method for Bayer domain is shown in figure 6. It consists of the following modules:

(1) *Noise Level Calculator*: The standard deviation of noise of each RGB channels is calculated for the *Filter Coefficient Calculator* and *Structure Classifier*.

(2) *Filter Coefficient Calculator*: The filter coefficients are generated by using pixel difference values within the filter kernel. The generation function is adapted to the calculated noise level.

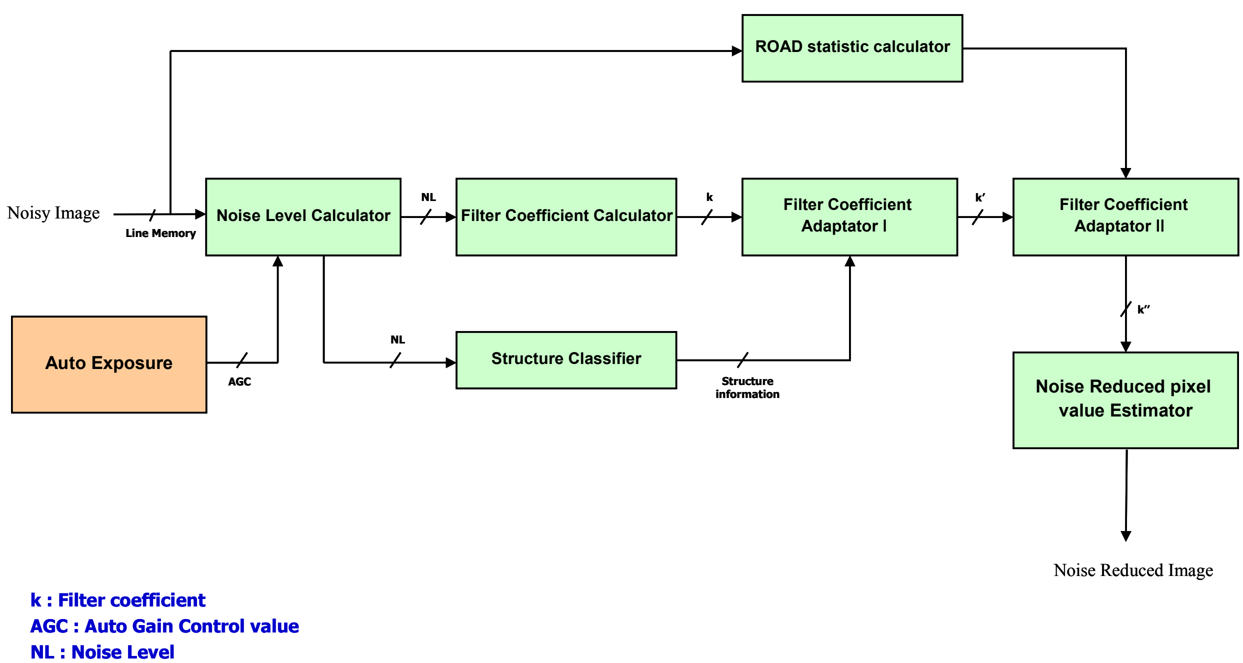


Figure 6. The proposed signal flow of noise reduction method for Bayer domain

(3) *Structure Classifier*: In order to exploit the local image statistics and structure, local region is classified as noisy region or texture region. If classified as texture region, the edge direction is also found for filter coefficients adaptation.

(4) *Filter Coefficient Adaptator I* : The filter coefficients generated by *Filter Coefficient Calculator* are adapted to structure information.

(5) *ROAD statistic calculator*: Rank-Ordered Absolute Differences (ROAD) statistic is very high for impulsive noise and much lower for uncorrupted pixels[5]. ROAD statistic is calculated to be used for *Filter Coefficient Adaptator II* .

(6) *Filter Coefficient Adaptator II* : The filter coefficients from *Filter Coefficient Adaptator I* are adapted to ROAD statistic.

(7) *Noise Reduced Pixel Value Estimator*: Weighted averaging is carried out to estimate noise reduced pixel value.

3.1. Noise Level Calculator

Let $\mathbf{x} = (x_1, x_2)$ be the location of the pixel of interest. Our noise model for noise reduction method for Bayer domain can be represented by

$$\begin{aligned} &s(\mathbf{x}) = f(\mathbf{x}) + \mathbf{n} \\ &\mathbf{n} \sim N(0, \sigma_{\mathbf{x}}^2) \\ &\sigma_{\mathbf{x}} = \eta(s(\mathbf{x})) \times \zeta(\mathrm{AGC}) \end{aligned} \tag{1}$$

where $s(\mathbf{x})$ is an observed noisy image from CMOS image sensor test module and $f(\mathbf{x})$ is an ideal image. $\mathbf{x}$ represents the location of pixel. $\mathbf{n}$ is a zero mean additive Gaussian noise whose standard deviation is a product of a function of $s(\mathbf{x})$ and a function of the AGC value. The function η is derived from the figure 4 and the function ζ is derived from the figure 5. They can be implemented in ISP by using Look-up Table (LUT). The calculated noise level $\sigma_{\mathbf{x}}$ is used for *Filter Coefficient Calculator* and *Structure Classifier*.

3.2. Filter Coefficient Calculator

The filter kernel is defined in Bayer domain as in figure 7. In low light condition, Gr-Gb channel discrepancy is very serious problem due to high signal amplification. Thus, in this paper, we define the filter kernel as in figure 7 to avoid Gr-Gb channel discrepancy.

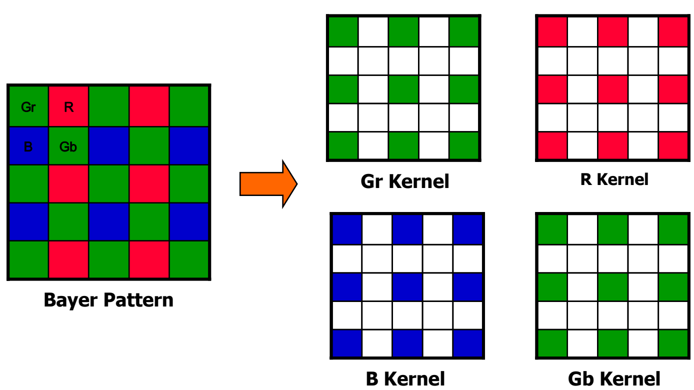


Figure 7. Bayer pattern filter kernel

Let $\Omega_{\mathbf{x}}$ be the set of pixel values in filter kernel centered at $\mathbf{x}$. For each pixel $\mathbf{m} \in \Omega_{\mathbf{x}}$ the filter coefficients are computed as

$$k(I_{\mathbf{m}} - I_{\mathbf{x}}) = \exp\left\{-\frac{1}{2}\left(\frac{I_{\mathbf{m}} - I_{\mathbf{x}}}{c \cdot \sigma_{\mathbf{x}}}\right)^2\right\} \tag{2}$$

where $I_{\mathbf{x}}$ is the pixel value of interest, $I_{\mathbf{m}}$ is a neighborhood pixel value, c is constant and $\sigma_{\mathbf{x}}$ is the calculated noise level. It is similar to the photometric distance measurement in Bilateral filter[4] but the filter coefficient calculation function (2) is spatially adapted to the characterized noise level. Since the denominator controls the amount of decay, the filter coefficients are adapted to the calculated noise level from *Noise Level Calculator*. Two dimensional LUT or piece-wise linear approximation can be used for implementation in ISP.

3.3. Structure Classifier

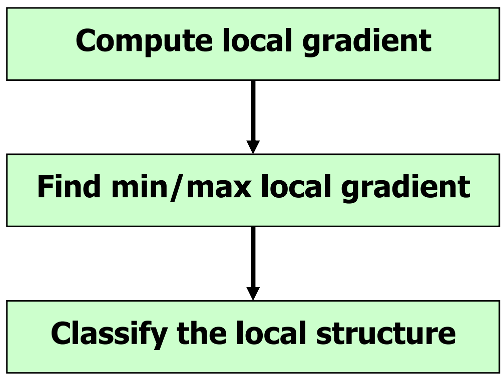


Figure 8. Block diagram of structure classification

Figure 8 shows the block diagram of structure classification. In order to compute local gradient, the index of filter kernel is defined as figure 9.

P_1		P_2		P_3
P_4		P_5		P_6
P_7		P_8		P_9

Figure 9. Index of filter kernel

The local gradients are computed as

$$\begin{array}{lll} G_{HOR\_1} = \left|P_4 - P_5\right| & G_{HOR\_2} = \left|P_5 - P_6\right| & G_{HOR} = G_{HOR\_1} + G_{HOR\_2} \\ G_{VER\_1} = \left|P_2 - P_5\right| & G_{VER\_2} = \left|P_5 - P_8\right| & G_{VER} = G_{VER\_1} + G_{VER\_2} \\ G_{NE\_1} = \left|P_3 - P_5\right| & G_{NE\_2} = \left|P_5 - P_7\right| & G_{NE} = G_{NE\_1} + G_{NE\_2} \\ G_{NW\_1} = \left|P_1 - P_5\right| & G_{NW\_2} = \left|P_5 - P_9\right| & G_{NW} = G_{NW\_1} + G_{NW\_2} \end{array} . \tag{3}$$

Then, $G_{\max}$ and $G_{\min}$ are defined as

$$\begin{aligned} G_{\max} &= Max(G_{HOR}, G_{VER}, G_{NE}, G_{NW}) \\ G_{\min} &= Min(G_{HOR}, G_{VER}, G_{NE}, G_{NW}) \end{aligned} . \tag{4}$$

The local structure is determined by

$$G_{\max} > T_{\sigma_{\mathbf{x}}} \tag{5}$$

where $T_{\sigma_{\mathbf{x}}}$ is pre-determined noise level adaptive threshold. The threshold $T_{\sigma_{\mathbf{x}}}$ is obtained by characterizing image sensor test module. If the local region satisfies the condition (5), it is classified as edge region. In this case, the minimum gradient $G_{\min}$ is used to find the orientation of edge. If the local region does not satisfy the condition (5), it is classified as noisy region.

3.4. Filter Coefficient Adaptator I

To adapt the local image structure, the filter coefficients computed by *Filter Coefficient Calculator* are modified according to the local structure information. We multiply the calculated filter coefficients by the structure adaptation kernel in figure 10. The coefficients $c_1,\ldots,c_8$ in the structure adaptation kernel are adaptively determined according to the structure information which is classified in section 3.3. There are five pre-determined sets of the coefficients $c_1,\ldots,c_8$ for each structure information, noisy region, vertical orientation region, horizontal orientation region, northwest orientation region and northeast orientation region. We call the modified filter coefficient k'.

c_1	c_2	c_3
c_4		c_5
c_6	c_7	c_8

Figure 10. Structure adaptation kernel

3.5. ROAD Statistic Calculator

The ROAD statistic provides a measure of how close a pixel value is to its four most similar neighbors[5]. The logic underlying the statistic is that unwanted impulses will vary greatly in intensity from most or all of their neighboring pixels, whereas most pixels composing the actual image should have at least half of their neighboring pixels of similar intensity, even pixels on an edge. For each pixel $\mathbf{m} \in \Omega_{\mathbf{x}}$ define $d_{\mathbf{x},\mathbf{m}}$ as the absolute difference between the pixel value of interest $I_{\mathbf{x}}$ and neighborhood pixel value $I_{\mathbf{m}}$, i.e.,

$$d_{\mathbf{x},\mathbf{m}} = \left| I_{\mathbf{x}} - I_{\mathbf{m}} \right| . \tag{6}$$

Sort the $d_{\mathbf{x},\mathbf{m}}$ values in increasing order and define

$$\mathrm{ROAD}(\mathbf{x}) = \sum_{i=1}^{4} r_i(\mathbf{x}) \tag{7}$$

where $r_i(\mathbf{x}) = i$th smallest $d_{\mathbf{x},\mathbf{m}}$ for $\mathbf{m} \in \Omega_{\mathbf{x}}$.

3.6. Filter Coefficient Adaptator II

After the ROAD statistic is calculated, the filter coefficient k' is adapted by the following algorithm in the figure 11. We call the modified filter coefficient k''.

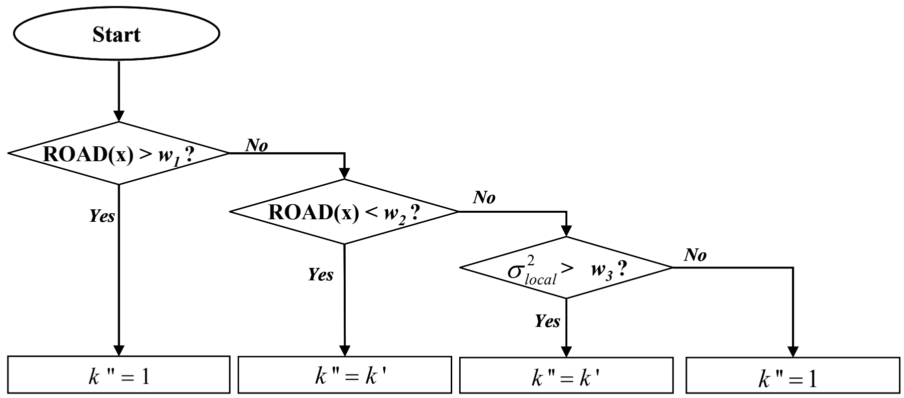


Figure 11. Filter coefficient adaptation algorithm to ROAD statistic

The parameters w_1, w_2 and w_3 depend on CMOS image sensor test module and calculated noise level. σ^2_{local} is local variance for the filter kernel centered at **x**.

3.7. Noise Reduced Pixel Value Estimator

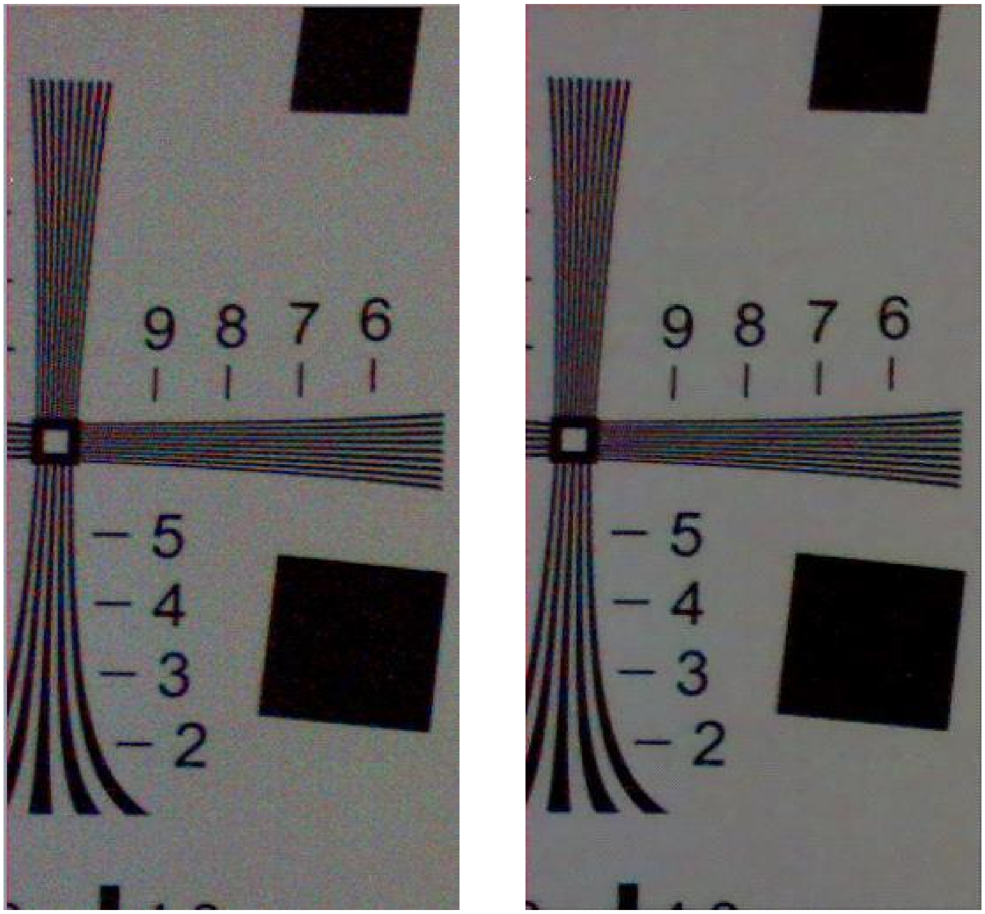
The estimated pixel $\hat{I}_{\mathbf{x}}$ is given by

$$\hat{I}_{\mathbf{x}} = \frac{1}{N-1} \sum_{\mathbf{m} \in \Omega_{\mathbf{x}}}^{N-1} [k'' I_{\mathbf{m}} + (1-k'') I_{\mathbf{x}}] \tag{8}$$

where N is the number of pixels of the filter kernel centered at **x**.

4. EXPERIMENTAL RESULTS

This section provides the simulation results of our proposed noise reduction method. We have tested the proposed algorithm for various images captured from Samsung 2M CMOS image sensor test module. Figure 12 shows the simulation results of the proposed method.


9 8 7 6
5
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9 8 7 6
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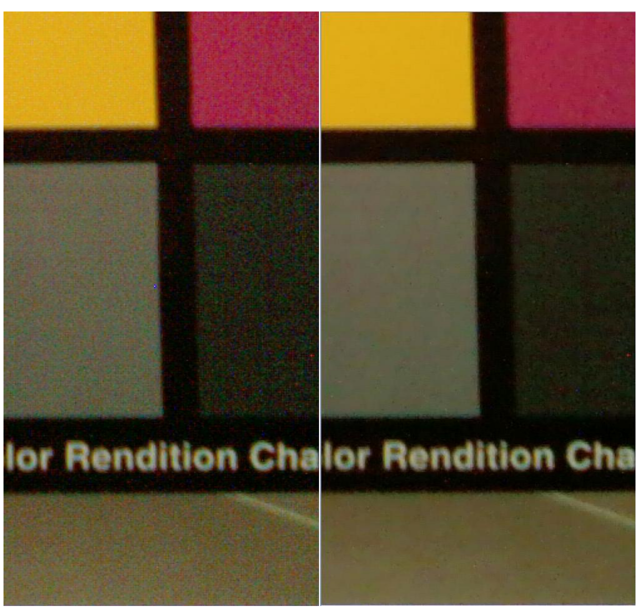
2

(a)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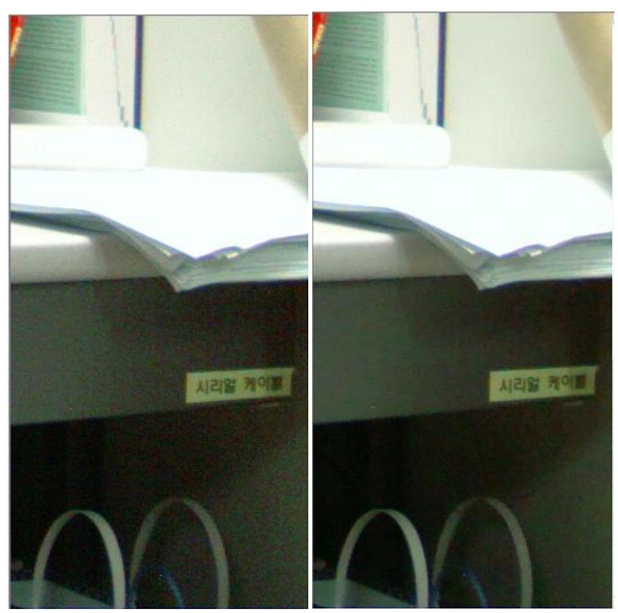
(b)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(c)

(d)

Figure 12. Simulation results of the proposed method

5. CONCLUSION

In this paper, we analyzed CMOS image sensor noise feature and proposed a new noise reduction method. The proposed method is especially developed for ISP in digital cameras and camera phones. This new method is easy to implement and has a low execution time. The experimental results indicate that our proposed method removes noise while effectively preserves details.

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