Noise Bias Compensation for Color Images after Tone Mapping

Sayaka Minewaki †, Yo Umeki †, Ryosuke Harakawa (member) † †, Masahiro Iwahashi (member) † †

Abstract An image after tone mapping (TM) has noise bias, i.e., noise values with a non-zero mean, because of the non-linearity of the TM function. Therefore, noise reduction filters based on the zero-mean assumption do not work well for such images. To overcome this limitation, noise bias compensation (NBC) divides pixels into subsets depending on their values and adaptively adjusts them using a Bayesian approach. However, previous studies on NBC target only gray-scale images and assume that the noise mean before TM is zero. This paper proposes a method for NBC that targets color images processed by TM with a non-zero noise mean. The proposed method adaptively calculates the compensation values based on prior knowledge that represents noise corresponding to each pixel value of RGB channels with a Bayesian approach. Experimental results show this Bayesian approach successfully reduces noise even for color images containing noise with a non-zero mean.

Key words: Noise reduction, tone mapping, Bayesian approach.

1. Introduction

Many methods for noise reduction (e.g., the Gaussian, median [1], regression [2, 3], and bilateral [4, 5]) filters use correlations between pixels. Recently, the non-local mean (NLM) filter [6] and the block-matching and three-dimensional (BM3D) filter [7] have attracted wide attention because of their high performance. The NLM filter replaces pixel-wise calculation with patch-wise calculation to perform noise reduction, and BM3D reduces noise by grouping 3D data arrays and collaborative filtering.

Most of the previous studies on noise reduction assume the noise to be i.i.d. additive white noise [1–7]. However, an image after tone mapping (TM) has noise bias (NB), i.e., noise values with a non-zero mean because of the non-linearity of the TM function. Existing noise reduction filters based on the zero-mean assumption do not work well for an image with NB. To the best of our knowledge, however, few methods have been proposed for reducing the noise in an image with NB.

We previously proposed noise bias compensation (NBC), which is a noise reduction scheme that takes into account the fact that the noise mean of an image after TM is a non-zero value [8–10]. NBC first divides all pixels into subsets according to their values. Then, NBC adaptively adjusts pixel values in each subset according to a Bayesian approach. Specifically, the compensation values are calculated based on the pixel values of an image without noise and the probabilistic distribution of noise before TM. NBC uses such information as the prior knowledge in the Bayesian approach. This noise reduction scheme is unique in that does not use correlations between pixels, unlike existing noise reduction filters. Therefore, we can collaboratively use NBC with such existing noise reduction filters to improve noise reduction performance. In fact, [8, 10] confirmed that the collaborative use of NBC with the NLM filter enables accurate noise reduction. However, our previously proposed NBC method [8–10] targets only gray-scale images.

In this paper, we propose a novel NBC that can be applied to color images as well. Figure 1 shows the scenario that this paper assumes. Specifically, we apply color quantization and TM to an original color image. Then, we perform NBC on the obtained image. Note that this study focuses on not the preservation of colors after NBC but on noise reduction.

Here, color quantization is a technique to meet the constraints of some hardware that can only display a limited number of colors [11]. Color quantization is used for preprocessing in applications such as object
recognition, image compression, and image retrieval. It is also used to accelerate color image processing tasks such as edge detection, image enhancement, histogram calculation, and color adjustment. However, there have been few studies on the reduction of color quantization noise [12]. Note that the mean of color quantization noise is not necessarily zero, and an image that has undergone color quantization and TM has NB.

The proposed method calculates the pixel compensation values from noise measured in the original and observed images for each component in the RGB color space. Previously proposed NBC methods assume that the mean of noise before TM is zero. Contrary to this, the NBC proposed in this paper does not assume that the mean of noise before TM is zero. Instead, it assumes that the mean of noise after TM is a non-zero value. Unlike existing methods (e.g., [1,4–7]), our NBC does not utilize the correlation between pixels. Because our NBC does not need a convolution operation, the computation is faster than such existing methods, and we can preserve the detailed texture of an image while reducing noise. Experimental results show that the proposed NBC reduces color quantization noise in a color-quantized image after TM.

The rest of this paper is organized as follows. Section 2 describes the problem settings of this work. In Section 3, the details of the proposed method are explained. Experimental results to verify the effectiveness of the proposed method are shown in Section 4. Concluding remarks are given in Section 5.

2. Problem Setting

As shown in Fig. 1, in this study, we first apply color quantization to an original image so that the image has \( n \) bit colors. Then, we apply TM to the color-quantized images. The noise in the color-quantized image is biased as a result of TM. Because the observed image has NB, our aim is to compensate for the NB. In this paper, we adopt median cuts [13] and gamma correction as the color quantization and TM function, respectively.

![Fig. 1](image)

**Fig. 1** Scenario assumed in this study.

This paper compensates NB of this image.

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2.1 Influence of TM on color quantization noise

Figures 2 and 3 show the process of obtaining the observed image (the target of NBC) and an example of the images, respectively. We define an original (24-bit color) image “Tree” (OpenEXR), (b) \( x_1 \): image after color quantization of \( x_0 \), (c) \( y_0 \): image after TM of \( x_0 \), and (d) \( y_1 \): observed image.

![Fig. 2](image)

**Fig. 2** Process of obtaining the observed image. CQ: mean color quantization; TM: tone mapping.

![Fig. 3](image)

**Fig. 3** Examples of images. (a) \( x_0 \): original image (b) \( x_1 \): image after color quantization of \( x_0 \), (c) \( y_0 \): image after TM of \( x_0 \), and (d) \( y_1 \): observed image.

\[
x_0(n) = \begin{bmatrix} R_{x_0}(n) \\ G_{x_0}(n) \\ B_{x_0}(n) \end{bmatrix} = \begin{bmatrix} R_{x_0}(n_1, n_2) \\ G_{x_0}(n_1, n_2) \\ B_{x_0}(n_1, n_2) \end{bmatrix}, \quad x_0 \in [0, X_{\text{MAX}}] \subseteq \mathbb{Z}.
\]
Here, $R_{x_0}(n)$, $G_{x_0}(n)$, and $B_{x_0}(n)$ are the RGB values of each pixel at a coordinate point $n = [n_1, n_2]$. Hereafter, we omit the coordinate $(n)$ and define $X_{MAX}$ to be 255. The original image shown in Fig. 3 (a) is a high-dynamic-range (HDR) image in OpenEXR format; however, this paper targets 24-bit color images. Therefore, in the experiments shown later, we normalized the HDR image so that it has a depth of 8 bits for each RGB component. Note that our NBC is designed for a color image and does not be specialized for an HDR image.

We denote the image obtained by applying color quantization (the median cut [13]) to original image $x_0$ by $x_1 (= MC(x_0, n))$. Here, $n$ is a parameter for determining the number of colors after the median cut. Figure 3 (b) shows the color-quantized image when $n = 5$. Furthermore, we define the color-quantization noise $\varepsilon_1$ as follows:

$$x_1 = x_0 + \varepsilon_1,$$

$$\begin{bmatrix}
R_{x_1} \\
G_{x_1} \\
B_{x_1}
\end{bmatrix} = \begin{bmatrix}
R_{x_0} + R\varepsilon_1 \\
G_{x_0} + G\varepsilon_1 \\
B_{x_0} + B\varepsilon_1
\end{bmatrix}.$$

When we denote a TM function (the gamma correction in this paper) by $f$, we can represent $y$, i.e., an image after TM as follows:

$$y = R(f(x)), \quad y \in [0, Y_{MAX}] \subseteq \mathbb{Z}.$$

Here, $R[\cdot]$ is a rounding function, and $Y_{MAX}$ is 255.

$$R[x] = \lfloor x + 2^{-1} \rfloor,$$

$$f(x) = \begin{cases} 
0 & x < 0 \\
Y_{MAX} \cdot \left( \frac{x}{X_{MAX}} \right)^{\frac{1}{\gamma}} & x \in [0, X_{MAX}] \\
Y_{MAX} & x > X_{MAX}.
\end{cases}$$

After applying TM to $x_1$, we obtain image $y_1$, as shown in Fig. 3 (c). In this figure, $\gamma$ is set to 3. Image $y_1$ can be represented as

$$y_1 = f(x_1) = y_0 + \delta_1,$$

$$\begin{bmatrix}
Ry_1 \\
Gy_1 \\
By_1
\end{bmatrix} = \begin{bmatrix}
Ry_0 + Ry_1 \\
Gy_0 + Gy_1 \\
By_0 + By_1
\end{bmatrix}.$$

Here, $y_0$ is the output noise in the image after the TM of $x_0$. Moreover, $\delta_1$ is the output noise in the observed image. Figure 3 (d) shows $y_0$, i.e., an image after TM of $x_0$.

### 2.2 Noise bias after TM

This section shows the probability mass function (PMF) of images before and after TM. Figure 4 shows pixel values before and after TM as well as a histogram of the output noise. Figure 4 (a) shows the histogram of $R_{x_1}$ after color quantization for pixels where $R_{x_0} = 60$. The mean after color quantization $E[R_{x_1}|R_{x_0}]$ is equal to 77.08. The histogram of color quantization noise $R\varepsilon_1$ is shown in Fig. 4 (b). In this case, the mean of color quantization noise $E[R\varepsilon_1|R_{x_0}]$ is equal to 17.08. These results show that the mean of noise after color quantization is a non-zero value. Figure 4 (c) shows the histogram of $Ry_1$, which comprises the observed pixel values after TM of $R_{x_1}$. For $Ry_0 = f(R_{x_0}) = 157.43$, $E[Ry_1|R_{x_0}]$ was 169.88. Furthermore, the histogram of the output noise $R\delta_1$ is shown in Fig. 4 (d). Here, $E[R\delta_1|R_{x_0}]$ is equal to 12.88. Figures 4 (b) and (d) confirm that an image after TM has NB even if the mean of noise in the color-quantized image before TM is not zero.

### 3. Proposed Method

This section reviews the conventional NBC (Section 3.1) and proposes an NBC that can be applied to color images (Section 3.2).
Concretely, we can write the following equation:

\[ y_2 = y_0 + \delta_2. \]  

Eq. (1)

Here, \( y_2 \), \( h(y_1) \), and \( \delta_2 \) are the pixel value after NBC, compensation function to calculate the compensation values, and output noise after NBC, respectively.

(2) Compensation function

The compensation value is the value of the NB, i.e., the mean of the noise in an image after TM. Note that the NB is not the mean of the output noise for all pixels in the observed image but is instead the mean of the \( \delta_1 \) corresponding to each pixel value \( y_1 \). Thus, the compensation value for the observed pixel value \( y_1 \) is defined as the conditional mean of the output noise \( \delta_1 \). Concretely, we can write the following equation:

\[ h(y_1) = E[\delta_1|y_1] = \frac{1}{|M_{y_1}|} \sum_{m \in M_{y_1}} \delta_1(m), \]

Eq. (2)

where \( M_{y_1} \) is a set of pixels with the observed pixel value \( y_1 \) and \( | \cdot | \) denotes the number of elements of the set. Here, the mapping from \( x_0 \) to \( \delta_1 \) is bijective. Based on Bayes’ theorem and the additive theorem of probability, we can rewrite Eq. (2) as

\[ h(y_1) = \frac{\sum_{x_0} P(x_0, y_1) \cdot \{y_1 - f(x_0)\}}{\sum_{x_0} P(x_0, y_1)}. \]

Eq. (3)

Here, the joint PMF \( P(x_0, y_1) \) is prior knowledge, obtained by using all pixel values of original image \( x_0 \) and observed image \( y_1 \).

3.2 NBC for color images (proposed method)

This section presents the proposed NBC for color images (see Fig. 6). By extending the conventional NBC, the proposed method calculates compensation values for each RGB component. Specifically, for the color quantized image \( x_1 \) obtained from the original color image \( x_0 \), we apply TM to each RGB component. For the observed image \( y_1 = [R_{y1}, G_{y1}, B_{y1}]^T \), we extend Eq. (1) and derive the proposed NBC as follows:

\[
\begin{bmatrix}
R_{y2} \\
G_{y2} \\
B_{y2}
\end{bmatrix} = \begin{bmatrix}
R_{y1} \\
G_{y1} \\
B_{y1}
\end{bmatrix} - \begin{bmatrix}
h(R_{y1}) \\
h(G_{y1}) \\
h(B_{y1})
\end{bmatrix} = \begin{bmatrix}
R_{y1} - h(R_{y1}) \\
G_{y1} - h(G_{y1}) \\
B_{y1} - h(B_{y1})
\end{bmatrix} = \begin{bmatrix}
R_{y0} + R\delta_2 \\
G_{y0} + G\delta_2 \\
B_{y0} + B\delta_2
\end{bmatrix}
\]

Eq. (4)

In the above equation, \( R_{y2}, G_{y2}, \) and \( B_{y2} \) are the respective RGB components of \( y_2 \), which is the image after NBC. Functions \( h(R_{y1}), h(G_{y1}), \) and \( h(B_{y1}) \) represent the compensation functions for each RGB component. In addition, \( R\delta_2, G\delta_2, \) and \( B\delta_2 \) are the respective RGB components of \( \delta_2 \), which is the output noise after NBC. Here, by extending Eq. (3), we define \( h(R_{y1}), h(G_{y1}), \) and \( h(B_{y1}) \) as follows:
and sated image patterns. However, the amount of header information is very small; thus, noise reduction becomes feasible without the restrictions of data storage and traffic. In fact, the majority of the header information is the prior knowledge shown in Fig. 7. The prior knowledge is represented as an image $256 \times 256$ pixels in size, in which most values are zero. Therefore, the amount of data is much smaller than that of $y_1$. For example, if $y_1$ is a full high-definition ($1,920 \times 1,080$ pixels) or 4K ($3,840 \times 2,160$ pixels) image, the percentage of pixels needed for the information is only approximately $3\%$ or $0.8\%$, respectively.

4. Experimental Results

4.1 Effect of the proposed method

Figure 8 shows a comparison of the NB of $y_1$ (the observed image) and NB of $y_2$ (the image after NBC) for each RGB component. The mean and variance of NB are shown in Table 1. These results show that the NB
Table 2  Differences in PSNR for other images. Here, we use Fig. 3 (d) as the observed image $y_1$.

|                  | All components | R component | G component | B component |
|------------------|----------------|-------------|-------------|-------------|
| NBC vs. observed | +0.3318        | +0.4957     | +0.5310     | +0.1257     |
| NBC+NLM vs. NLM  | +0.4003        | +0.6391     | +0.6477     | +0.1250     |
| NBC+BM3D vs. BM3D| +0.4042        | +0.7969     | +0.7946     | +0.1023     |
| NBC+NLM vs. NBC  | +0.0412        | +0.0883     | +0.0482     | +0.0136     |
| NBC+BM3D vs. NBC | +0.0529        | +0.3308     | +0.1470     | +0.0285     |
| NBC+BM3D vs. NBC+LNM | -0.0083     | +0.2425     | +0.0988     | +0.0149     |

images after NBC decreased. We also confirm that the mean and variance become zero after NBC.

4.2 Quality of images after NBC

We evaluated the image quality before and after NBC using the following equation for peak signal-to-noise ratio (PSNR):

$$PSNR = 10 \log_{10} \frac{Y_{MAX}^2}{\text{Var}[\delta(n)]}$$

Figure 9 shows the image after NBC ($y_2$) of the observed image ($y_1$) shown in Fig. 3 (c). The PSNRs for $y_1$ and $y_2$ are 24.3316 (dB) and 24.6633 (dB), respectively. Thus, we confirmed that the PSNR was increased by 0.3318 (dB) by the NBC. In particular, the effects on the R and G components are substantial. This is because the NB was decreased by NBC, as described in Section 4.1.

In Fig. 10, we present the effect of $\gamma$ in the TM function. This figure shows means, maximum values, and minimum values of the PSNR increase for seven images (“Tree”, “Couple”, “Girl”, “Mandrill”, “Pepper”, “PrismsLenses”, and “Rec709”). We can see that larger values of $\gamma$ lead to a higher image quality after NBC. For $\gamma = 6$, the PSNR for each of the RGB components of $y_2$, i.e., the image after NBC, increased by 0.3806 (dB), 0.4828 (dB), and 0.2927 (dB) on average. It can be seen that the effects of NBC are more substantial for the R and G components than they are for the B component.

In Fig. 11, we verify the effect on the number of colors $n$ after the median cut. As in Fig. 10, this figure shows means, maximum values, and minimum values of the PSNR increase for the seven images. Note that larger values of $n$ lead to smaller subtractive colors. We confirmed that the image quality after NBC is improved even for various values of $n$.

4.3 Effect of the combination of NBC with other noise reduction filters

As explained in Section 1, we can collaboratively use NBC with existing noise reduction filters based on pixel correlations. Here, we evaluate the effectiveness of combining NBC with the NLM filter and BM3D. Figure 12 shows the result when we use Fig. 3 (d) as observed image $y_1$. The PSNR is compared in Fig. 13. In addition, Table 2 shows the difference of PSNR. In Figs. 12 and 13 and Table 2, “observed”, “NLM”, “BM3D”, “NBC”, “NBC+NLM”, and “NBC+BM3D” represent the observed image $y_1$, the image obtained by applying the NLM filter to $y_1$, the image obtained by applying BM3D to $y_1$, the image after NBC $y_2$, the image obtained by applying the NLM filter to $y_2$, and the image obtained by applying BM3D to $y_2$, respectively. As described in Section 4.2, the PSNR of “NBC” is superior than that of “observed”. Furthermore, PSNRs of “NBC+NLM” and “NBC+BM3D” are higher than those of “NLM” and “BM3D”, respectively. In addition, the PSNRs of “NBC+NLM” and “NBC+BM3D” are also higher than that of “NBC”. These results show that the combination use of NBC and other filters is more effective for noise reduction than the use of only NBC or the other filter.

Figures 14 and 15 show the ideal images, observed images, and denoised images for other images (“Couple”, “Girl”, “Mandrill”, “Pepper”, “PrismsLenses”, and “Rec709”). Also, Fig. 16 shows the enlarged partial details of Fig. 14 (a)-(g). We can see that the combination of our NBC with other noise reduction filters avoids over-smoothing more suitably than the only use of the filters. Figure 17 shows the quantitative evaluation results, and Table 3 shows the differences in PSNR shown in Fig. 17. For all results, we confirmed that the PSNR for “NBC” is superior to that of “observed”. At the
Fig. 10 Improvement of the PSNR by NBC: the effect of $\gamma$ in the TM function. (a) Images before (after) NBC $y_1 (y_2)$, (b) R component, (c) G component, and (d) B component. The dots show means of the PSNR increase for seven images ("Tree", "Couple", "Girl", "Mandrill", "Pepper", "PrismsLenses", and "Rec709"). The bars show maximum values and minimum values of the PSNR increase for the seven images.

Fig. 11 Improvement of the PSNR by NBC: the effect of $n$ in the median cut. In this figure, we set $\gamma = 3$. The notation is the same as in Fig. 10.

Fig. 12 Results of a combination of NBC and other filters. Here, we use Fig. 3 (d) as observed image $y_1$. In the same time, we can see that PSNRs of “NBC+NLM” and “NBC+BM3D” are higher than those of “NLM” and “BM3D”, respectively. Furthermore, we find that “NBC+BM3D” is superior than “NBC+NLM” in most cases. As a result, we confirm the effectiveness of the proposed NBC for color images.

5. Conclusion

This paper proposed an NBC that can be applied to color images. Using a Bayesian approach, the proposed method adaptively calculates the compensation values for noise in the RGB components of the input and observed images. Previous studies on NBC target only gray-scale images and assume that the mean of noise before TM is zero. Contrary to this, we targeted color
| Table 3 | Differences in PSNR. |
|---------|-------------------|
|          | (a) “Couple” (SIDBA) |          |          |          |          |
|          | All components     | R component | G component | B component |
| NBC vs. observed | +0.1243 | +0.3129 | +0.0808 | +0.1039 |
| NBC+NLM vs. NLM  | +0.1564 | +0.2693 | +0.0904 | +0.1431 |
| NBC+BM3D vs. BM3D | +0.2490 | +0.4392 | +0.1186 | +0.2370 |
| NBC+NLM vs. NBC   | +0.5009 | +0.8242 | +0.4614 | +0.3471 |
| NBC+BM3D vs. NBC  | +0.9703 | +1.3752 | +0.8727 | +0.5657 |
| NBC+BM3D vs. NBC+NLM | +0.4094 | +0.5510 | +0.4413 | +0.2186 |
| (b) “Girl” (SIDBA) |          |          |          |          |
|          | All components     | R component | G component | B component |
| NBC vs. observed | +0.1847 | +0.0523 | +0.2817 | +0.1176 |
| NBC+NLM vs. NLM  | +0.2049 | +0.0394 | +0.3379 | +0.1022 |
| NBC+BM3D vs. BM3D | +0.3185 | +0.0913 | +0.4058 | +0.2064 |
| NBC+NLM vs. NBC   | +0.2647 | +0.8167 | +0.2475 | +0.1043 |
| NBC+BM3D vs. NBC  | +0.8478 | +1.3631 | +0.7589 | +0.4626 |
| NBC+BM3D vs. NBC+NLM | +0.5831 | +0.5464 | +0.5115 | +0.3582 |
| (c) “Mandrill” (SIDBA) |          |          |          |          |
|          | All components     | R component | G component | B component |
| NBC vs. observed | +0.0323 | +0.0211 | +0.0271 | +0.0414 |
| NBC+NLM vs. NLM  | +0.0556 | +0.0509 | +0.0553 | +0.0581 |
| NBC+BM3D vs. BM3D | +0.1239 | +0.1425 | +0.1337 | +0.1610 |
| NBC+NLM vs. NBC   | +0.2728 | +0.5901 | +0.0823 | +0.2044 |
| NBC+BM3D vs. NBC  | +0.6726 | +0.7633 | -0.5527 | +0.4045 |
| NBC+BM3D vs. NBC+NLM | +0.3998 | +0.1732 | -0.6349 | +0.2001 |
| (d) “Pepper” (SIDBA) |          |          |          |          |
|          | All components     | R component | G component | B component |
| NBC vs. observed | +0.2753 | +0.0315 | +0.2747 | +0.3399 |
| NBC+NLM vs. NLM  | +0.2731 | +0.0321 | +0.2618 | +0.4021 |
| NBC+BM3D vs. BM3D | +0.3241 | +0.0610 | +0.3325 | +0.4030 |
| NBC+NLM vs. NBC   | +0.1676 | +0.4955 | +0.0863 | +0.1650 |
| NBC+BM3D vs. NBC  | +0.5078 | +0.9417 | +0.4293 | +0.5588 |
| NBC+BM3D vs. NBC+NLM | +0.3402 | +0.4462 | +0.3430 | +0.3938 |
| (e) “PrismsLenses” (OpenEXR) |          |          |          |          |
|          | All components     | R component | G component | B component |
| NBC vs. observed | +0.3156 | +0.3395 | +0.2379 | +0.3604 |
| NBC+NLM vs. NLM  | +0.3329 | +0.3572 | +0.2460 | +0.3852 |
| NBC+BM3D vs. BM3D | +0.2775 | +0.3240 | +0.2889 | +0.2192 |
| NBC+NLM vs. NBC   | +0.0697 | +0.0548 | +0.1051 | +0.0547 |
| NBC+BM3D vs. NBC  | +0.3139 | +0.3181 | +0.3825 | +0.2787 |
| NBC+BM3D vs. NBC+NLM | +0.2442 | +0.2633 | +0.2733 | +0.2239 |
| (f) “Rec709” (OpenEXR) |          |          |          |          |
|          | All components     | R component | G component | B component |
| NBC vs. observed | +0.1504 | +0.1013 | +0.1805 | +0.1568 |
| NBC+NLM vs. NLM  | +0.1574 | +0.0958 | +0.1940 | +0.1548 |
| NBC+BM3D vs. BM3D | +0.1759 | +0.0153 | +0.2453 | +0.1935 |
| NBC+NLM vs. NBC   | +0.2248 | +0.3210 | +0.2471 | +0.1643 |
| NBC+BM3D vs. NBC  | +0.6077 | +1.0798 | +0.5324 | +0.3770 |
| NBC+BM3D vs. NBC+NLM | +0.3829 | +0.7588 | +0.2853 | +0.2127 |

images obtained by applying TM to images with a non-zero noise mean. Experimental results show that the proposed method (in particular, the combined use of our method and the NLM filter or BM3D) is effective for noise reduction. Future work includes the extension of our NBC to videos.

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Fig. 14 Results of a combination of NBC and other filters for "Couple" ((a)-(g)), "Girl" ((h)-(n)), and "Mandrill" ((o)-(u)).
Fig. 15 Results of a combination of NBC and other filters for “Pepper” ((a)-(g)), “PrismsLenses” ((h)-(n)), and “Rec709” ((o)-(u)).
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Sayaka Minewaki received her B.Eng. and M.Eng. degrees in Engineering from Kyushu Institute of Technology in 2001 and 2003, respectively. In 2006, she finished a Ph.D. program without a dissertation at the Department of Artificial Intelligence, Kyushu Institute of Technology. In 2006, she joined the Department of Computer Science and Engineering, National Institute of Technology, Yuge College, where she served concurrently as a Lecturer. From 2016 to 2018, she joined the Nagaoka University of Technology, where she is currently an Assistant Professor of the Department of Electrical, Electronics and Information Engineering. From 2016, she has been with the Department of Computer Science and Engineering, National Institute of Technology, Yuge College. Her research interests are in the fields of digital signal processing, image compression, and natural language processing.

Yo Umeki received his B.Eng. and M.Eng degrees from Nagaoka University of Technology, Nagaoka, Japan, in 2015 and 2017, respectively. From 2019, he has been Assistant Professor with the Department of Computer Science and Engineering, National Institute of Technology, Yuge College. He is also currently a doctoral course student in the Department of Information Science and Control Engineering, Nagaoka University of Technology. His research interests are in the area of saliency detection.

Ryosuke Harakawa received his B.S., M.S., and Ph.D. degrees in electronics and information engineering from Hokkaido University, Japan, in 2013, 2015, and 2016, respectively. He is currently an Assistant Professor with the Department of Electrical, Electronics, and Information Engineering, Nagaoka University of Technology. His research interests include multimedia information retrieval and Web mining. He is a member of the IEEE, IEICE and the Institute of Image Information and Television Engineers (ITE).

Masahiro Iwahashi received his B.Eng., M.Eng., and D.Eng. degrees in electrical engineering from Tokyo Metropolitan University, Tokyo, Japan, in 1988, 1990, and 1996, respectively. In 1990, he joined Nippon Steel Company Ltd. Since 1993, he has been with the Nagaoka University of Technology, Nagaoka, Japan, where he is currently a Professor with the Department of Electrical, Electronics and Information Engineering. His research interests include the areas of digital signal processing, multi-rate systems, and image compression. He is currently a Senior Member of the IEEE and IEICE. He is also a member of the Asia Pacific Signal and Information Processing Association (APSIPA) and the Institute of Image Information and Television Engineers (ITE).