PAPER

Joint Deblurring and Demosaicing Using Edge Information from Bayer Images

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SUMMARY Most images obtained with imaging sensors contain Bayer patterns and suffer from blurring caused by the lens. In order to convert a blurred Bayer-patterned image into a viewable image, demosaicing and deblurring are needed. These concepts have been major research areas in digital image processing for several decades. Despite their importance, their performance and efficiency are not satisfactory when considered independently. In this paper, we propose a joint deblurring and demosaicing method in which edge direction and edge strength are estimated in the Bayer domain and then edge adaptive deblurring and edge-oriented interpolation are performed simultaneously from the estimated edge information. Experimental results show that the proposed method produces better image quality than conventional algorithms in both objective and subjective terms.
key words: deblurring, demosaicing, Bayer pattern, constraint least square, edge adaptive process

1. Introduction

In modern digital still cameras (DSCs) including mobile cameras, single imaging sensors such as CCD (charge-coupled devices) or CMOS (complementary metal-oxide semiconductors) have been widely used to reduce cost and size. The Bayer pattern [1], which uses only one color component among the primary color components at a given pixel position, is a well known color filter array (CFA). However, Bayer patterned images suffer from several kinds of noise and blurring effects. Especially, the optical blurring caused by a camera's lens is a major degrading factor. In order to change a raw image obtained from an imaging sensor into an image suitable for the human visual system, demosaicing and deblurring are two necessary procedures. These procedures have been studied by many researchers for several decades [2]–[19].

Most demosaicing algorithms have been based on correlations between color channels, which means that the color ratio or color difference is of a constant value within a local area [2], [3]. This basic premise is not effective in edge regions since the color ratio or color difference has a different value when it is calculated in these regions. Therefore, local edge information has been considered in various demosaicing approaches. In weighted average approaches [4], [5], the missing pixels are obtained from the weighted average of the neighboring pixels by using various edge indicator functions. Edge directional interpolation

approaches [6]–[9] have been proposed to reconstruct sharp edges and reduce Moiré effects in edge patterns. Since the missing pixels are interpolated according to the estimated edge direction, performance depends on the accuracy of the estimated edge direction.

Deblurring refers to obtaining an original image from a blurred image. If it is assumed that blurring can be modeled as a linear process, deblurring presents the inverse problem of ill-posedness [10]. Generally, the regularization method is used to change ill-posedness to well-posedness. A number of approaches [11], [12] have focused on determining the regularization parameter that controls the data fidelity and a priori knowledge such as smoothness term. In order to improve the edges and avoid undesirable amplitude of noise factors, some methods [13], [14] use edge adaptive deblurring, which incorporates local edge characteristics as a priori knowledge.

As described above, most deblurring methods are performed without considering the Bayer pattern [15], [16] and most demosaicing methods are performed by assuming the input is deblurred and noise free. When dealing with blurred Bayer pattern images, demosaicing and deblurring are sequentially performed. In this case, visual demosaicing artifacts are amplified by the deblurring process. Recently, methods combining deblurring and demosaicing have been proposed to avoid this problem [17]–[19]. Paliy et al. [17] presented a joint deblurring and demosaicing method based on local polynomial approximation (LPA) and intersection of confidence intervals (ICI). In previous work [18], [19], the least squares regularization approach was used to combine deblurring and demosaicing. These joint methods produced better image quality than sequential methods. However, performance can be further improved by using a spatially adaptive regularization parameter because the previous researchers performed the regularization process with a fixed regularization parameter in both the flat and edge regions. In addition, these joint methods required time consuming processes such as LPA and ICI [17] or iterative regularization [18], [19], where a number of iterations were required to reach a converged solution.

In this paper, we propose a joint deblurring and demosaicing algorithm. The proposed method is motivated by the similarity between the deblurring and demosaicing methods, since the local edge information represents a major way of improving performance. For this purpose, the edge direction and edge strength are estimated in a given Bayer pattern image by using a projection-based edge estimation method.

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Then edge adaptive deblurring and edge oriented interpolation are processed simultaneously from the estimated edge information. To save processing time, we construct a predefined table of constraint least squares (CLS) filters in which various regularization parameters and directional high pass operators are utilized. Then, an edge adaptive CLS (EACLS) filter to remove blurring is selected from the table.

The rest of this paper appears as follows. In Sect. 2, an observation model of the blurred Bayer image is described. To restore the original full-color image, the proposed method is described in Sect. 3. First, the overall structure of the proposed method is presented. Then, detailed descriptions of a predefined EACLS filter table is given. Next, a joint method of deblurring and demosaicing is presented. In Sect. 4, experimental results are given to verify the performance of the proposed method. Finally, conclusions are presented in Sect. 5.

2. Problem Statement

In imaging systems such as digital still cameras, the image degradation process can generally be modeled by a linear blur [10]. An image degraded by blurring can be expressed as:

$$\mathbf{g}^i = \mathbf{H}^i \mathbf{f}^i \quad i \in \{R, G, B\}, \quad (1)$$

where $\mathbf{f}$ and $\mathbf{g}$ represent the lexicographical vectors of the original image and the observed image, respectively. The matrix $\mathbf{H}$ denotes the linear spatially invariant blur (optical blur). The superscript i denotes the color channel: red (R), green (G), or blue (B). By stacking the vectors $\mathbf{f}^i$ and $\mathbf{g}^i$, $\mathbf{f}$ and $\mathbf{g}$ can be described as:

$$\begin{aligned} \mathbf{f} &= [\mathbf{f}^R^T \quad \mathbf{f}^G^T \quad \mathbf{f}^B^T]^T, \\ \mathbf{g} &= [\mathbf{g}^R^T \quad \mathbf{g}^G^T \quad \mathbf{g}^B^T]^T. \end{aligned} \quad (2)$$

Then, the blurred image $\mathbf{g}$ is sampled with a Bayer pattern where each pixel has one color component among three primary color components. Consequently, the observation model of the imaging system shown in Fig. 1 is:

$$\mathbf{g}_{\text{CFA}} = \mathbf{D}_{\text{CFA}} \mathbf{H} \mathbf{f} + \mathbf{n}, \quad (3)$$

where $\mathbf{g}_{\text{CFA}}$ and $\mathbf{n}$ represent the lexicographical vectors of the observed CFA image and the additive Gaussian noise, respectively. $\mathbf{D}_{\text{CFA}}$ denotes a downsampling matrix with the Bayer CFA pattern and $\mathbf{H}$ corresponds to the block diagonal matrix: $\mathbf{H} = \text{diag}[\mathbf{H}^R, \mathbf{H}^G, \mathbf{H}^B]$. Based on the image

Fig. 1 Observation model of the imaging system.

degradation model shown by Eq. (3), the desired image can be estimated intuitively by using demosaicing and deblurring.

3. Joint Deblurring and Demosaicing

The overall structure of the proposed method is depicted in Fig. 2. From the existed color information, the G channel is considered before the R or B channels because the G channel contains brightness information in twice as many samples as the R or B channels. In the proposed method, the local edge information is first extracted from the blurred Bayer image as shown in Fig. 2 ① and then the obtained edge information is used to estimate the parameters of the filter and the weights for fusing. At the same time, the G channels are initially computed in Fig. 2 ② according to horizontal and vertical directions, respectively because the deblurring process requires full G channel information at each pixel location. In Fig. 2 ③, regularization parameter (α) and edge directional high pass operator (C_{EA}) are estimated with local edge information and an EACLS filter is obtained from the table of CLS filters. Then, the EACLS filter is used to remove the blurring of the initial G channels and the R/B channels in the blurred Bayer image as shown in Fig. 2 ④. In order to obtain the original G channel, the directionally separated G channels are fused in Fig. 2 ⑤ according to the edge strength and the edge direction. For the R and B channel processes, the results of the G channel process are used to improve deblurring performance and interpolation quality of the R and B channels. In Fig. 2 ⑥, the original R (or B) channel information is obtained by using the smoothness color difference between the deblurred G and deblurred R (or B) channels. Last, a deblurred color image is produced.

3.1 Predefined EACLS Filter Table

The CLS is a well-known way of solving the deblurring problem. Generally, the cost function of the CLS [10] appears in matrix form:

$$\min \{ \|\hat{\mathbf{g}}^i - \mathbf{H}^i \mathbf{f}^i\|^2 + \alpha \|\mathbf{C} \mathbf{f}^i\|^2 \}, \quad (4)$$

where $\mathbf{f}^i$ represents the lexicographical vector of the original image and $\hat{\mathbf{g}}^i$ denotes the lexicographical vector of the

Fig. 2 Overall block diagram of the proposed method.

blurred image, which is estimated by interpolation of the nearby pixels because missing color components exist in the observed image $\mathbf{g}_{CFA}$. The superscript i denotes the primary color channels R , G , and B . $\mathbf{H}^i$ and $\mathbf{C}$ represent the blur and high pass operator matrices, respectively. $\mathbf{H}^i$ and $\mathbf{C}$ are part of a linear and spatially invariant system and can be represented as a block circulant matrix. $\mathbf{H}^i$ is assumed as a known parameter.

The solution of Eq. (4) is obtained by finding the gradient of $\mathbf{f}^i$ to Eq. (4) and making this gradient zero.

$$[\mathbf{H}^{iT} \mathbf{H}^i + \alpha \mathbf{C}^T \mathbf{C}] \mathbf{f}^i = \mathbf{H}^{iT} \hat{\mathbf{g}}^i. \quad (5)$$

Since the block circulant matrix can be diagonalized by using the discrete Fourier Transform [10], Eq. (5) is rewritten by diagonalizing $\mathbf{H}^i$ and $\mathbf{C}$. That is:

$$\begin{aligned} \mathcal{H}_{CLS}^i(\omega_1, \omega_2) &= \frac{\mathcal{F}^i(\omega_1, \omega_2)}{\hat{\mathcal{G}}^i(\omega_1, \omega_2)} \\ &= \frac{\mathcal{H}^{i*}(\omega_1, \omega_2)}{|\mathcal{H}^i(\omega_1, \omega_2)|^2 + \alpha |\mathcal{C}(\omega_1, \omega_2)|^2}, \end{aligned} \quad (6)$$

where the asterisk $*$ represents a complex conjugate. $\mathcal{F}^i$, $\hat{\mathcal{G}}^i$, $\mathcal{H}^i$, and $\mathcal{C}$ denote the frequency responses of $\mathbf{f}^i$, $\hat{\mathbf{g}}^i$, $\mathbf{H}^i$, and $\mathbf{C}$, respectively. $\mathcal{H}_{CLS}^i$ is the frequency response of the inverse filter of $\mathbf{H}^i$.

The CLS filter h_{CLS}^i is obtained by transforming $\mathcal{H}_{CLS}^i$ into a finite spatial filter. First, the inverse discrete Fourier Transform (IDFT) is performed to transform the $\mathcal{H}_{CLS}^i$ from the frequency domain to the spatial domain. However, the result of the IDFT is generally an infinite signal so the infinite filter has to be truncated. The CLS filter is estimated by applying a windowing operation to the result of the IDFT. However, unwanted artifacts such as ringing effects are generated according to the type of the window function during the windowing operation. Thus, the windowing function whose shape is gradationally reduced to the boundary of the window is used to reduce the ringing artifacts. Among various windowing functions, the Gaussian window is used in this paper. The CLS filter size is determined according to the window size. Generally, the CLS filter can achieve better reconstruction performance by using wider windows since the windowed CLS filter becomes similar to the overall CLS filter. However, if the window size increases, the complexity of hardware implementation also increases. According to the infinite CLS filter, the significant coefficients of the CLS filter are distributed in vicinity of the center point, which shows that some coefficients of the CLS filter can substitute the overall CLS filter with small errors that can be ignored. Therefore, the window size is determined to have the windowed CLS filter be similar to the overall CLS filter with respect to the quality of the restored image. In this paper, the window size is chosen as 13×13 for the CLS filter.

The characteristics of the CLS filter are determined according to α and $\mathbf{C}$ of Eq. (6). According to the CLS method [11], [12], a small α results in an edge enhanced image, while a large α results in a smoothed image. Thus,

Fig. 3 Illustration of the CLS filter: (a) cross section along the horizontal axis of the CLS filter with various α and isodirectional $\mathbf{C}$, and (b) cross section along the horizontal and vertical axes of the CLS filter with horizontal $\mathbf{C}$ and $\alpha = 1.0$. The horizontal $\mathbf{C}$ is determined by using Eq. (16) with $w_{CH} = 2$ and $w_{CV} = 0$.

a CLS filter with a small α is close to a high pass filter, while a CLS filter with a large α is close to a low pass filter. In Fig. 3 (a), an example of the CLS filters with various α and isodirectional $\mathbf{C}$ is illustrated. The graph denotes cross section of the CLS filter along the horizontal axis. As shown in Fig. 3 (a), the CLS filter has more negative coefficients as α decreases. These negative coefficients produce sharp edge transitions in the edge region. According to the CLS method [13], [14], edge directional $\mathbf{C}$ can improve edge performance by preventing an oversmoothed solution. In Fig. 3 (b), an example of a CLS filter with $\alpha = 1$ and a horizontal $\mathbf{C}$ to detect vertical gradient is illustrated. 'Hor' and 'Ver' in the graph legends indicate cross section of the CLS filter along the horizontal and vertical axes, respectively. If the CLS filter is applied to the horizontal edge, the image is smoothed only in the horizontal direction, which generally preserves the edges.

As discussed above, the reconstruction performance of the CLS filter can be improved by using the α and $\mathbf{C}$ values, which corresponds to the edge characteristics. However, the transforming process to obtain the CLS filters requires a large computational load and thus the predefined EACLS filter table is constructed by using various regularization parameters ($0 < \alpha \leq 1$) and edge directional high pass op-

erators (C_{EA}) before performing the proposed method. In this paper, the horizontal and vertical directions for C_{EA} are considered since the G channel information is estimated by either horizontal or vertical interpolations at each pixel location due to Bayer sampling. Then, the EACLS filter is edge adaptively selected according to α and C_{EA} , which are estimated from the edge strength and edge direction values at each pixel location.

3.2 Jointly Deblurring and Demosaicing Considering Edge Information

With the edge information estimated by the projection based method, deblurring and demosaicing are jointly performed as a single system. An example to illustrate the proposed method is shown in Fig. 4. The edge information in each direction is first estimated from blurred Bayer images. Here, we estimate the parameters for deblurring and demosaicing by using each direction and edge strength. α map and C_{EA} map are used to determine the EACLS filter. The red, green, and black colors of the C_{EA} map denote the horizontal, vertical, and isotropic high pass operators, respectively. w_H map and w_V map represent the weights for edge directional interpolation. Last, the output image is generated by simultaneously performing deblurring and demosaicing.

Fig. 4 An example to illustrate the proposed method with edge information extracted from a blurred Bayer image. The edge information was used to obtain α , C_{EA} , w_H , and w_V . α map and C_{EA} map (red, green, and black of the C_{EA} map denote horizontal, vertical, and isodirectional high pass operator, respectively) were used to determine the EACLS filter. w_H map and w_V map represent weights for edge directional interpolation. The output image was generated by simultaneously performing deblurring and demosaicing.

3.2.1 Projection-Based Edge Estimation from Bayer Pattern Images

The edge information, including edge direction and edge strength, is estimated by using the projection-based edge estimation method since the directional average of the projection process can be used to reduce estimation errors of the edge information as caused by noise factors of the given Bayer images. In order to obtain local edge information, edge orientation is quantized into four particular directions: horizontal, vertical, and diagonal. Then, the respective edge strengths of the directions are estimated by the directional projection method. By employing the edge strengths, the edge information is founded at each pixel position.

The proposed projection-based edge estimation method is composed of three steps: calculation of directional projection, calculation of gradient, and estimation of edge strength and edge direction. First, directional projection is defined as the sums of the pixel value along any particular direction. In this paper, four directions such as horizontal, vertical and diagonal directions are considered and the proposed method performs projections of the pixels inside the directional masks. In Fig. 5 (a), an example of the directional masks is shown. In this case, diagonal projections need more line memory than horizontal and vertical projections for hardware implementation. In order to reduce the hardware resources for the directional projections, the shape of the windows is fixed for all the projections. Thus, the projection data is normalized to the total number of pixels inside the directional mask because the total number of pixels differs according to the direction and size of the mask. Then, the directional projection data is calculated as:

$$\begin{aligned}
 P^H(k) &= \sum_{(x,y) \in A_{Hor}^G(k)} \mathbf{g}_{CFA}(x,y) / \text{Num}(A_{Hor}^G(k)), \\
 P^V(k) &= \sum_{(x,y) \in A_{Ver}^G(k)} \mathbf{g}_{CFA}(x,y) / \text{Num}(A_{Ver}^G(k)), \\
 P^{DN}(k) &= \sum_{(x,y) \in A_{DiagN}^G(k)} \mathbf{g}_{CFA}(x,y) / \text{Num}(A_{DiagN}^G(k)), \\
 P^{DP}(k) &= \sum_{(x,y) \in A_{DiagP}^G(k)} \mathbf{g}_{CFA}(x,y) / \text{Num}(A_{DiagP}^G(k)),
 \end{aligned} \tag{7}$$

where P^H , P^V , P^{DN} , and P^{DP} denote projections in the horizontal direction, the vertical direction, the diagonal direction with a negative slope, and the diagonal direction with a positive slope, respectively. $\mathbf{g}_{CFA}$ represents the blurred Bayer image. x and y represent the horizontal and vertical pixel indices, respectively. A denotes the directional mask whose direction is represented by the subscript of A . A^G denotes the G channel inside A and $\text{Num}(A^G)$ represents the number of pixels of A^G . k represents the displacement of the directional mask. An example of directional projection is illustrated in Fig. 5 (b) where the solid arrow denotes direction of the directional mask.

Fig. 5 Illustration of the directional projection process: (a) directional masks, and (b) directional projection.

Secondly, the gradient is calculated with the directional projection data, which represents the difference value along the perpendicular direction of the projection direction. Since the image is smoothed only in the direction of the edges, difference values along the perpendicular direction of edges are large. The gradient is estimated by finding the maximum value of difference between the center pixel and the neighboring pixels because the gradient is defined as the difference in neighboring pixels. Since the respective calculation processes of the four directions are exactly the same, we will only describe the horizontal process in this paper. The gradient of the horizontally projected data is calculated as:

$$D_{pH} = \max(D_{max\mathcal{L}}, D_{c\mathcal{L}min}), \quad (8)$$

where

$$\begin{aligned} D_{max\mathcal{L}} &= P_{max}^H - P_{center}^H, \\ D_{c\mathcal{L}min} &= P_{center}^H - P_{min}^H. \end{aligned} \quad (9)$$

P_{center}^H denotes a horizontally projected data factor in the center position. P_{min}^H and P_{max}^H represent the min and max values of the projection data, respectively.

$$\begin{aligned} P_{min}^H &= \min\{P^H(1), \dots, P^H(5)\}, \\ P_{max}^H &= \max\{P^H(1), \dots, P^H(5)\}. \end{aligned} \quad (10)$$

Finally, the edge strength for each direction is obtained from the computed gradients and the edge direction at each pixel position is estimated by finding the maximum value among the gradients. For mathematical tractability, the edge strength for each direction is defined as a comparative value between the gradients.

$$\begin{aligned} Estr_H &= \max(D_{pH} - D_{pV}, 0), \\ Estr_V &= \max(D_{pV} - D_{pH}, 0), \\ Estr_{DN} &= \max(D_{pDN} - D_{pDP}, 0), \\ Estr_{DP} &= \max(D_{pDP} - D_{pDN}, 0). \end{aligned} \quad (11)$$

$Estr$ denotes the edge strength of each direction and the subscripts of $Estr$ represent the direction of the projected data factors. As a consequence of the edge strength, the edge direction is determined by finding a direction whose edge strength is the max value of the directional edge strength.

3.2.2 Edge Adaptive Parameter Estimation for EACLS Filter

In this paper, the EACLS filter, whose characteristics are determined by the regularization parameter α and the directional high pass operator C_{EA} , is used to improve the edges and avoid undesirable levels of noise amplitude. For this purpose, the α and C_{EA} values of the EACLS filter are edge adaptively determined at each pixel position. Thus, the α and C_{EA} values are estimated from the edge strength and edge direction values.

The regularization parameter α is a key issue to solve the blurring effects because it controls the data fidelity term $\|\hat{\mathbf{g}}^i - \mathbf{H}^i \mathbf{f}^i\|^2$ and the smoothness term $\|\mathbf{C} \mathbf{f}^i\|^2$. The data fidelity term refers to the mean square error between the blurred image $\hat{\mathbf{g}}^i$ and the synthesized image $\mathbf{H}^i \mathbf{f}^i$. The smoothness term restricts the characteristics of the available solutions from having a priori knowledge of the ideal image. The large regularization parameter value, which more reflects the smoothness term in the solution than the data fidelity term, is good for reducing noise in flat regions. The small regularization parameter value, which more reflects the data fidelity term in the solution than the smoothness term, is good for sharpening the edges in the edge regions. Thus, the regularization parameter is an inverse proportion to the smoothness term and is proportional to the data fidelity term.

$$\alpha \propto \frac{\|\hat{\mathbf{g}}^i - \mathbf{H}^i \mathbf{f}^i\|^2}{\|\mathbf{C} \mathbf{f}^i\|^2}. \quad (12)$$

The smoothness term measures the high frequency components of the image. Since these high frequency components are observed in the edge regions, the edge strength is substituted for the smoothness term. Thus, the regularization parameter is inversely proportional to the edge strength. Since the data fidelity term represents the energy of the noise of the observed image, the regularization parameter is a proportion to the variance of noise. Equation (12) can be rewritten as:

$$\alpha \propto \frac{var_n}{Estr}, \quad (13)$$

where $Estr$ is obtained from the edge strength values of Eq. (11).

$$Estr = \max(Estr_H, Estr_V, Estr_{DN}, Estr_{DP}). \quad (14)$$

The var_n value denotes the variance of noise in the given image.

Finally, the regularization parameter can be estimated by using the proportional relationship:

$$\alpha = \min\left(\frac{var_n}{\max(Estr, \tau) \times T_E}, 1\right), \quad (15)$$

where T_E is used to aggrandize the edge strengths to improve weak edge regions. In order to prevent obtaining a solution that is too smooth in the weak edge regions, the regularization parameter is limited by one for small $Estr$ values.

Fig. 6 The regularization parameter α plot: $Estr$ varies while $var_n = 0.5$ and $T_E = 1$.

τ is used to prevent division by zero when $Estr$ is zero. An example of the regularization parameter (where $Estr$ varies while $var_n = 0.5$ and $T_E = 1$) is illustrated in Fig. 6.

In typical regularization, the smoothness term operates under the assumption that the image is globally smooth. However, this assumption can make it difficult to obtain sharp solutions when dealing with edge regions. In order to prevent an oversmoothed solution, the smoothness term is determined according to local edge characteristics. Thus, the smoothness term is controlled by the edge-adaptive filter C_{EA} to preserve the edge components. In this paper, the horizontal and vertical directions for C_{EA} are considered since the G channel information is estimated by either horizontal or vertical interpolations at each pixel location due to Bayer downsampling. Then, the C_{EA} value is estimated by:

$$C_{EA} = C_{ISO} + C_H * w_{CH} + C_V * w_{CV}, \quad (16)$$

where

$$\begin{aligned} C_{ISO} &= \begin{bmatrix} -0.25 & -0.25 & -0.25 \\ -0.25 & 2 & -0.25 \\ -0.25 & -0.25 & -0.25 \end{bmatrix}, \\ C_H &= \begin{bmatrix} 0 & 0 & 0 \\ -0.25 & 0.5 & -0.25 \\ 0 & 0 & 0 \end{bmatrix}, \\ \text{and } C_V &= \begin{bmatrix} 0 & -0.25 & 0 \\ 0 & 0.5 & 0 \\ 0 & -0.25 & 0 \end{bmatrix}. \end{aligned} \quad (17)$$

C_{ISO} , C_H , and C_V represent isodirectional, horizontal, and vertical C values, respectively. Although there can sometimes be several high pass operators, we use C_{ISO} , C_H , and C_V for mathematical tractability. Since the image is smoothed only in the direction of the edges in order to preserve the edge components, C_{ISO} , C_H , and C_V are used to penalize the high frequency components in the isodirectional, horizontal, and vertical directions, respectively. The w value denotes the weights of each directional high pass operator. Thus, w is proportional to edge strength and defined as:

$$w_{CH} = \frac{Estr_H}{Estr_H + Estr_V}, \text{ and } w_{CV} = \frac{Estr_V}{Estr_H + Estr_V}. \quad (18)$$

Note that a large computational load is required to compute the C_{EA} according to the weights, as they appear in Eq. (18), since the edge strengths have many different values at each pixel position. Therefore, in order to easily implement the proposed method, the C_{EA} is quantized into three cases: isodirectional C , horizontal C , and vertical C . Then, respective weights are determined by the edge strengths.

$$\begin{cases} w_{CH} = 0, w_{CV} = 0 & \text{if } \max(Estr_H, Estr_V) < Th \\ w_{CH} = 2, w_{CV} = 0 & \text{if } Estr_H > Estr_V \\ w_{CH} = 0, w_{CV} = 2 & \text{if } Estr_V > Estr_H \end{cases}, \quad (19)$$

where Th denotes the threshold value that is used to determine the isodirectional direction.

3.2.3 Edge Adaptive Interpolation and Deblurring

In this paper, interpolation and deblurring are edge adaptively performed with the estimated edge information. The interpolation for the missing color components is based on edge directional interpolation approaches that are used to reconstruct sharp edges and reduce Moiré effects in the edge patterns. Deblurring is performed with the EACLS filter with a lower computational complexity level compared to the iterative regularization method. In order to reduce the computational load, a lookup-table is used for the prepared EACLS filter, which is constructed with various regularization parameters and directional high pass operators.

From the existing color information, the G channel process for interpolation and deblurring is considered before the R or B channels. The G channel process is composed of three steps: initial estimate of G channel information, edge adaptive deblurring, and edge directional interpolation. In the deblurring process, full G channel information is required at each pixel location. However, the G channel information in the given Bayer image is spatially disjointed and blurred. This problem is solved by using an initial estimate of the G channel information. Thus, the missing G channel information is initially estimated in the horizontal and vertical directions, respectively. The directional G channel is computed as:

$$\begin{aligned} \bar{g}_H^G(x, y) &= \frac{\mathbf{g}_{CFA}^G(x-1, y) + \mathbf{g}_{CFA}^G(x+1, y)}{2} \\ &\quad + \frac{2 \cdot \mathbf{g}_{CFA}^i(x, y) - \mathbf{g}_{CFA}^i(x-2, y) - \mathbf{g}_{CFA}^i(x+2, y)}{4}, \\ \bar{g}_V^G(x, y) &= \frac{\mathbf{g}_{CFA}^G(x, y-1) + \mathbf{g}_{CFA}^G(x, y+1)}{2} \\ &\quad + \frac{2 \cdot \mathbf{g}_{CFA}^i(x, y) - \mathbf{g}_{CFA}^i(x, y-2) - \mathbf{g}_{CFA}^i(x, y+2)}{4}, \end{aligned} \quad i \in \{R, B\} \quad (20)$$

where $\mathbf{g}_{\text{CFA}}$ represents the blurred Bayer image and the superscript of $\mathbf{g}_{\text{CFA}}$ represents the primary color channel. $\hat{\mathbf{g}}_{\text{H}}^G$ and $\hat{\mathbf{g}}_{\text{V}}^G$ denote the horizontally and vertically interpolated G channels, respectively.

$\hat{\mathbf{g}}_{\text{H}}^G$ and $\hat{\mathbf{g}}_{\text{V}}^G$ are degraded by blurring because the interpolation process is performed by using blurred color information. Thus, deblurring with the EACLS filter is applied to $\hat{\mathbf{g}}_{\text{H}}^G$ and $\hat{\mathbf{g}}_{\text{V}}^G$. The deblurring process is represented as:

$$\begin{aligned}\hat{\mathbf{f}}_{\text{H}}^G &= \hat{\mathbf{g}}_{\text{H}}^G * h_{\text{EACLS}}^G(\alpha, C_{\text{EA}}), \\ \hat{\mathbf{f}}_{\text{V}}^G &= \hat{\mathbf{g}}_{\text{V}}^G * h_{\text{EACLS}}^G(\alpha, C_{\text{EA}}),\end{aligned}\quad (21)$$

where $\hat{\mathbf{f}}_{\text{H}}^G$ and $\hat{\mathbf{f}}_{\text{V}}^G$ denote the deblurred values of $\hat{\mathbf{g}}_{\text{H}}^G$ and $\hat{\mathbf{g}}_{\text{V}}^G$, respectively. h_{EACLS}^G is the EACLS filter whose shape is changed by α and C_{EA} . α and C_{EA} are estimated from the Bayer image by using Eqs. (15) and (16) at each pixel location so that the EACLS filter is edge adaptively performed in order to improve the reconstruction performance of the edge regions. In order to reduce the computational load, the EACLS filter is obtained by selecting a spatial filter from the EACLS filter table in accordance with α and C_{EA} . As discussed above, the edge adaptive deblurring process is based on regularized filtering. In this case, the filter size plays a key role in the reconstruction performance since the filtering process works on neighborhood pixels. However, the regularized filter is generally an infinite filter and has negative coefficients, which generate local gradients to improve edge information. Thus, the regularized filter has to be truncated for hardware implementation and sufficient filter size is necessary for the regularized filter to achieve satisfactory performance. As described in Sect. 3.1, the EACLS filter is designed to be 13×13 , as determined by considering the characteristics of the regularized filter.

The original G channel, $\hat{\mathbf{f}}^G$ is finally estimated by fusing $\hat{\mathbf{f}}_{\text{H}}^G$ and $\hat{\mathbf{f}}_{\text{V}}^G$ according to the edge direction:

$$\hat{\mathbf{f}}^G = w_{\text{H}} \cdot \hat{\mathbf{f}}_{\text{H}}^G + w_{\text{V}} \cdot \hat{\mathbf{f}}_{\text{V}}^G, \quad (22)$$

where w_{H} and w_{V} denote the weights of the horizontal and vertical directions, respectively. The weights play a key role in improving the resolution of the demosaiced color image. In order to improve interpolation performance, some fusing rules [6]–[9] are used to combine directionally interpolated values. Especially, the fusing strategy for weak edge regions and pattern edge regions is significantly considered since the edge information in these regions is insufficient due to Bayer downsampling and thus it is not easy to determine edge direction without error. However, if the Bayer image is degraded by blurring effects, weak edge information is more affected by the blurring effects than dominant edge information. The weak edge regions become similar to the flat regions, which simplifies the fusing problem. Moreover, if the fusing process is performed with inaccurate edge information, visual artifacts are noticeably generated because the directional interpolation error is larger than even the average interpolation error and the error is amplified by the deblurring process. For these reasons, the Bayer image is divided

into dominant edge regions and undetermined regions. The undetermined regions include flat region and weak edge region. In the dominant edge regions along horizontal or vertical directions, the edge strength of either horizontal or vertical directions has larger value than the edge strengths of two diagonal directions since the edge strength of cross edge direction has a maximum value. Thus, the dominant edge regions are determined by comparing the directional edge strengths. After the edge types are categorized with the classified region types, edge directional interpolation and even average interpolation are performed for the dominant edge regions and the undetermined regions, respectively. Thus, the weights are defined as:

$$\begin{aligned}w_{\text{H}} &= \frac{Estr_{\text{H}}}{Estr_{\text{H}} + Estr_{\text{V}}}, & w_{\text{V}} &= \frac{Estr_{\text{V}}}{Estr_{\text{H}} + Estr_{\text{V}}} \\ && & \text{if } Estr \neq \max(Estr_{\text{DN}}, Estr_{\text{DP}}), \\ w_{\text{H}} &= 0.5, & w_{\text{V}} &= 0.5 \\ && & \text{if } Estr = \max(Estr_{\text{DN}}, Estr_{\text{DP}}).\end{aligned}\quad (23)$$

$Estr$ represents the edge strength value at each pixel location and it is obtained from Eq. (14).

The original R and B channels are estimated with the estimated $\hat{\mathbf{f}}^G$ value and the color difference model. Since the correlation between each deblurred color channel has to be preserved, the blurring of the R and B components at the R and B pixel positions is first removed before estimating the missing R or B channels. The deblurred R and B values at the R and B positions are computed with the EACLS filter.

$$\begin{aligned}\hat{\mathbf{f}}^{\text{R}} &= \hat{\mathbf{g}}^{\text{R}} * h_{\text{EACLS}}^{\text{R}}(\alpha, C_{\text{EA}}) & \text{at R position,} \\ \hat{\mathbf{f}}^{\text{B}} &= \hat{\mathbf{g}}^{\text{B}} * h_{\text{EACLS}}^{\text{B}}(\alpha, C_{\text{EA}}) & \text{at B position.}\end{aligned}\quad (24)$$

Then, the original R and B values at the missing R and B positions are obtained by the weighted average of the color difference value in the deblurred image.

$$\hat{\mathbf{f}}^{\text{R}}(x, y) = \hat{\mathbf{f}}^G(x, y) - \frac{1}{\text{Num}(A_{\text{NN}})} \sum_{(i,j) \in A_{\text{NN}}} \hat{K}r(i, j), \quad (25)$$

where A_{NN} denotes a set of neighboring R pixels at the B or G locations and $\text{Num}(A_{\text{NN}})$ represents the number of pixels of A_{NN} . The relationship between the $\hat{\mathbf{f}}^{\text{R}}$ and $\hat{\mathbf{f}}^{\text{B}}$ values and the $\hat{\mathbf{f}}^G$ values is:

$$\begin{aligned}\hat{K}r(x, y) &= \hat{\mathbf{f}}^G(x, y) - \hat{\mathbf{f}}^{\text{R}}(x, y), \\ \hat{K}b(x, y) &= \hat{\mathbf{f}}^G(x, y) - \hat{\mathbf{f}}^{\text{B}}(x, y),\end{aligned}\quad (26)$$

where $\hat{K}r$ and $\hat{K}b$ denote the color difference value.

4. Experimental Results

The performance of the proposed method was tested with the Kodak PhotoCD image set. We converted the Kodak images into blurred Bayer images by performing an image degradation process. First, the Kodak images were blurred

Fig. 7 13×13 PSF of the blurring kernel used for evaluating the proposed method.

by optical blurring that is represented by a point spread function (PSF) of an imaging system. The PSF was theoretically estimated by using wave optics approach. The frequency response of the PSF refers to the optical transfer function (OTF). The OTF of diffraction-limited optics with a circular exit pupil [20] is defined as:

$$\mathcal{H}_{OTF}(\omega_1, \omega_2) = \frac{2}{\pi} \left[\cos^{-1} \left(\frac{\rho}{\rho_c} \right) - \frac{\rho}{\rho_c} \left[1 - \left(\frac{\rho}{\rho_c} \right)^2 \right]^{1/2} \right], \quad (27)$$

where $\rho = (\omega_1^2 + \omega_2^2)^{1/2} = \rho_c / (1/\lambda N)$ and the cutoff frequency is $\rho = 1$ or $\rho_c = 1/(\lambda N)$. N is the f-number of the optics and λ is the wavelength of light. Then, the PSF was obtained by transforming $\mathcal{H}_{OTF}$ into a finite spatial filter. The transforming process is similar to those discussed in Sect. 3.1. As shown in Fig. 7, 13 × 13 PSF of the blurring kernel was used for evaluating the proposed method. Then, the blurred image was downsampled with the Bayer pattern and 30-dB Gaussian noise was added to the blurred Bayer image. We evaluated the reconstruction results in both subjective and objective ways. The color peak-to-peak signal to noise ratio (CPSNR), the normalized color difference (NCD), and root mean square error (RMSE) were used to objectively evaluate the improvement of the proposed algorithm.

To verify the performance of the proposed method, sequential methods for deblurring and demosaicing were compared. According to the processing sequence of deblurring and demosaicing, pre-deblurring (a sequential method performing deblurring before demosaicing) and post-deblurring (a sequential method performing deblurring after demosaicing) were implemented for comparison. Here, demosaicing was performed by using edge directional interpolation. We also compared the performance of the proposed method with conventional joint deblurring and demosaicing algorithms proposed by Paliy et al. [17] and by Ma and Reeves [19].

There are several parameters in the proposed method. Since the characteristics of the predefined EACLS filter depended on the parameters and the performance of the pro-

Fig. 8 Effect of EACLS filter size on CPSNR. The size of the EACLS filter varies from 5 × 5 to 17 × 17.

posed method was highly dependent on the edge information obtained from the given Bayer image, it was difficult to find the theoretical optimal one. Thus, the parameters were set empirically and tested with various images to obtain the best results. In the proposed method, a predefined EACLS filter table for the known blur was constructed as described in Sect. 3.1. The size of the EACLS filter was determined according to the size of the Gaussian window which was used to truncate an infinite signal. Since the windowed EACLS filter obtained from the wider window appeared similar to the overall EACLS filter, the EACLS filter size severely impacted the performance of the reconstructed image. In Fig. 8, we presented the CPSNR values of the proposed method by varying the size of the EACLS filter to analyze the effect of the filter size on the image quality. As shown in Fig. 8, the CPSNR value was higher as the filter size increased. In our observations, there was little improvement when the size was larger than 13 × 13. Therefore, we set the size as 13 × 13, as a compromise between performance and hardware complexity. α in Eq. (6) represents the regularization parameter. For constructing the EACLS filter table, α was in the range [0–1] which was divided into equal parts. The EACLS filter contained more negative coefficients as α decreased. Since these negative coefficients produced sharp edge transitions in the edge regions, the α value close to 0 was the important factor in determining performance. In Fig. 9, we presented the CPSNR values of the proposed method by varying the constants which were used to divide the range [0–1] into equal parts. The dividing constants were set as 4, 8, 16, 32, and 64. In this case, the α value that was closer to 0 was considered for constructing the EACLS filter table as the dividing constant increased. As shown in Fig. 9, the CPSNR value scored higher as the dividing constant increased to 32. Although the EACLS filter with a small α value such as 0.015625 achieved enhanced edge contrast, the noise factor in the flat region was boosted, which decreased the quality of the reconstructed image. For this reason, the CPSNR value of the dividing constant 64 was lower than that of the dividing constant 32. Therefore, we set the dividing constant as 32, as a compromise between objective and subjective performance. C in Eq. (6) repre-

Fig. 9 CPSNR comparison according to dividing constant which is used to divide the range [0–1] into equal part. The dividing constant varies from 4 to 64.

Fig. 10 CPSNR comparison according to the size of the directional mask. The size of local region varies from 5×5 to 9×9 .

sents the high pass operator. Although there can be several high pass operators, the isodirectional, horizontal, and vertical C values are considered for mathematical tractability and for reducing computational load. The directional C s were designed by using Eqs. (16)–(19). A in Eq. (7) represents the directional mask used for computing the directional projection data. Since the edge information was estimated by the gradient computed with directional projection data, the mask size impacted the accuracy of the edge estimation. The mask size for each direction was determined in the local region used in the experiments. In Fig. 10, we presented the CPSNR values of the proposed method by varying the size of the considered local region to analyze the effect of the mask size on the image quality. As shown in Fig. 10, the CPSNR value rose as the local region size increased. In our observation, there was little improvement when the size of the considered local region was larger than 5×5 . Therefore, the directional masks were determined in the 5×5 local region, as a compromise between performance and hardware complexity. Also, τ in Eq. (15) represents a constant for preventing zero division and T_E in Eq. (15) was used to aggrandize the edge strength to improve edge regions. τ and T_E were set as 0.1 and 1, respectively. For certain applications, T_E can be set as over 1 to further enhance edge regions.

Fig. 11 The partially magnified images of Kodak 5 from (a) the original image, (b) the demosaiced image, (c) pre-deblurring, (d) post-deblurring, (e) the proposed method with $T_E = 1$, and (f) the proposed method with $T_E = 8$.

Th in Eq. (19) denotes the threshold value to determine the isodirectional direction. Th was set as 2 for 8-bit images degraded by 30-dB Gaussian noise. Since the edge strength rose as the noise level increased, Th can be set as over 2 to correctly classify the isodirectional direction.

Figures 11 and 12 show the partially magnified results of the proposed method and the sequential approach methods for detailed edge regions in the Kodak 5 image and for the flat region in the Kodak 3 image. Figures 11(a) and 12(a) represent the original image, respectively. Figures 11(b) and 12(b) show the demosaiced image that was obtained with edge directional interpolation. In pre-deblurring, post-deblurring, and the proposed method in Figs. 11(c)–11(f), the edge information was improved by the deblurring process of each method. However, visible artifacts including zipper artifacts remained on the edge region in Fig. 11(c) because the correlation between the color channels was broken by performing deblurring on the sub-sampled color channel. Fig. 11(d) is too smooth in the edge region since the compensated high frequency was limited to prevent boosted artifacts. In Fig. 11(e) which was reconstructed by the proposed method with $T_E = 1$, the dominant edge information was improved without artifacts, while the weak edge region in the upper right of the image lost some fine details. In the weak edge regions, the edge strengths have small values, which made α a large value. For this reason, some details of the weak edge regions were lost. In Fig. 11(f), edge strengths of the weak edge regions were aggrandized by using $T_E = 8$, which resulted in satisfactory

Fig. 12 The partially magnified images of Kodak 3 from (a) the original image, (b) the demosaiced image, (c) pre-deblurring, (d) post-deblurring, (e) the proposed method with $T_E = 1$, and (f) the proposed method with $T_E = 8$.

performance for both the dominant edge and the weak edge. In Figs. 12(c) and 12(d), the details of the cloud were improved by compensating the high frequency properties of the cloud but the noise level was also boosted. As shown in Figs. 12(e) and 12(f), the proposed method with $T_E = 1$ achieved fine results without the boosted noise, while the result of the proposed method with $T_E = 8$ was degraded by the boosted noise. These experimental results demonstrate that the proposed method can achieve better performance for edge and flat regions than sequential methods. By adjusting the parameter T_E , the reconstruction performance of the weak edge information can be improved under permissible noise limits. In this paper, the proposed method was performed with $T_E = 1$ in order to obtain satisfactory results for both edge regions and flat regions because flat regions occupy large areas of images in general.

Figures 13 and 14 demonstrate some improvements over the sequential approach methods. In Fig. 13, we compared the CPSNR values of the proposed method and the sequential approach method for the Kodak PhotoCD image set. The higher CPSNR value represents the fact that the error between the reconstructed image and the original image is less. The CPSNR graphs show that the proposed method improved the quality of the reconstructed image. In Fig. 14, we also compared the NCD values of the proposed method and conventional methods. The NCD is a measurement of the perceptual errors between the original and the reconstructed image. A lower NCD value shows that the restored image has fewer color artifacts, which are

Fig. 13 CPSNR comparison of the proposed method and conventional approaches (pre-deblurring and post-deblurring) on the 24 test images.

Fig. 14 NCD comparison of the proposed method and conventional approaches (pre-deblurring and post-deblurring) on the 24 test images.

side effects of the false estimation of the edge direction in demosaicing. The NCD graphs indicate that the blurred Bayer image was reconstructed with a reduced color artifact by the proposed method. In Table 1, the RMSE values for the R channel, G channel, and B channel were compared, respectively. Though the proposed method does not achieve the lowest RMSEs for all the channels in Kodak 2, 4, 14, 15, 22, and 24, it produced the lowest RMSEs for all the channels in all the other Kodak images. On the other hand, for Kodak 2, 4, 14, 15, 22, and 24, the pre-deblurring and post-deblurring methods achieved the lowest RMSE value for only one channel but the proposed method accomplished the lowest RMSEs in the other channel. The proposed method achieved average RMSE improvements over the pre-deblurring and post-deblurring methods. Therefore, the proposed method outperformed the sequential methods in the majority of the Kodak images.

Figure 15 depicts partially magnified results of the proposed method and the conventional joint deblurring and demosaicing method for the Kodak 19 image. Figure 15(a) represents the original image. Though weak edge information existed in the roof of Fig. 15(a), this information was degraded by optical blurring and then this weak edge region became similar to the flat regions. Thus, the roof region

Table 1 RMSE comparison of the proposed method and sequential approaches (pre-deblurring and post-deblurring) on the 24 test images.

	Demaicing			Pre-deblurring			Post-deblurring			Proposed		
	R	G	B	R	G	B	R	G	B	R	G	B
1	10.95	10.98	10.89	7.88	6.63	8.02	7.58	7.49	7.55	6.31	6.14	6.18
2	6.18	5.28	5.42	5.74	3.80	4.51	4.77	4.07	4.21	4.80	3.53	3.54
3	5.42	5.10	5.17	5.02	4.25	5.01	4.26	4.02	4.34	3.99	3.55	4.05
4	6.03	5.29	5.59	5.63	4.50	5.16	4.57	4.03	4.14	4.79	3.80	3.86
5	11.32	10.88	10.94	8.32	6.93	8.48	7.43	7.04	7.40	6.57	6.14	6.62
6	9.63	9.37	9.29	7.65	6.62	7.62	7.05	6.93	7.09	5.95	5.90	6.08
7	5.99	5.61	5.97	5.13	4.00	5.53	4.04	3.75	4.18	3.69	3.30	3.85
8	14.78	14.44	14.66	11.11	8.78	10.81	10.28	9.96	10.31	8.41	8.01	8.24
9	6.10	5.98	5.89	5.12	3.99	5.11	4.19	4.03	4.19	3.55	3.33	3.63
10	6.06	5.95	6.11	5.06	4.15	5.10	4.24	4.05	4.33	3.71	3.45	3.75
11	8.34	7.94	7.91	6.54	5.58	6.28	6.03	5.78	5.86	5.30	4.97	5.01
12	5.71	5.62	5.73	5.20	4.37	5.27	4.25	4.10	4.29	3.85	3.55	3.75
13	14.30	14.08	14.44	10.68	10.00	11.15	10.54	10.48	10.95	9.25	9.35	9.69
14	9.25	8.32	8.34	7.71	6.33	7.48	6.76	6.14	6.47	6.80	5.85	6.45
15	7.49	6.87	7.07	8.48	7.23	7.88	6.63	6.16	6.15	6.67	5.79	5.78
16	6.58	6.39	6.40	5.19	4.66	5.25	5.09	5.02	5.08	4.32	4.28	4.35
17	6.45	6.40	6.60	5.71	5.16	5.97	5.07	5.03	5.15	4.73	4.66	4.69
18	9.47	9.24	9.42	7.57	6.61	7.75	6.91	6.73	7.16	6.49	6.15	6.66
19	9.52	9.16	9.07	7.04	5.52	6.41	6.52	6.29	6.31	5.24	4.92	4.88
20	7.72	7.50	7.65	7.75	7.17	8.11	6.37	6.34	6.50	5.45	5.49	5.71
21	8.76	8.57	8.61	6.79	5.90	6.90	6.17	6.13	6.33	5.19	5.16	5.41
22	7.17	6.94	7.24	6.75	5.24	6.37	5.55	5.11	5.50	5.58	4.64	5.15
23	5.52	4.90	5.17	5.75	4.34	5.88	4.51	3.75	4.11	4.37	3.21	3.67
24	9.98	10.28	11.56	9.00	8.23	9.88	7.84	7.84	8.96	7.92	7.59	8.47
avg.	8.28	7.96	8.13	6.95	5.83	6.91	6.11	5.84	6.11	5.54	5.11	5.39

Fig. 15 Partially magnified images of the Kodak 19 images obtained with (a) the original image, (b) Paliy's method [17], (c) Ma's method [19], and (d) the proposed method.

was considered a flat region when evaluating the reconstruction results. Figures 15(b) and 15(c) represent the reconstructed results obtained by Paliy's method [17] and Ma's method [19], respectively. In Paliy's method in Fig. 15(b), the edge information of the fence region improved by compensating for the high frequency component but visible artifacts remained in the vertical edge region including the high frequency region. On the other hand, the vertical edge of the fence region was improved without visible artifacts in Ma's method and the proposed method in Figs. 15(c) and 15(d). In the flat regions of the roof and sky, the boosted noise artifacts are shown in Figs. 15(b) and 15(c). On the other hand, the proposed method successfully reconstructed the edge information while reducing visible artifacts, as shown in Fig. 15(d).

Fig. 16 CPSNR comparison of the proposed method and conventional methods (Paliy's method [17] and Ma's method [19]) on the 24 test images.

Fig. 17 NCD comparison of the proposed method and conventional methods (Paliy's method [17] and Ma's method [19]) on the 24 test images.

In Figs. 16 and 17, we compared the CPSNR and NCD results with the proposed method and conventional methods (Paliy's method [17] and Ma's method [19]). The CPSNR graph shows that the proposed method scored the highest value for most of the Kodak images. In the NCD graph, the proposed method achieved the lowest value for the majority of the Kodak images. In Table 2, the RMSE values for the R channel, G channel, and B channel were compared, respectively. Though Paliy's method and Ma's method achieved the lowest RMSE value in Kodak 1, 2, 4, 13, 14, 17, 18, 22, and 24, the proposed method produced the lowest RMSEs for all channels in all the other Kodak images. The proposed method achieved average RMSE improvements over Paliy's method and Ma's method. Therefore, the proposed method produced better image quality than the conventional joint methods for the majority of the Kodak images.

In Table 3, the average processing time is presented in order to compare the computational complexity of the deblurring and demosaicing methods. The experiments were performed on a PC equipped with an Intel Core2 Quad Q8200 CPU. The CPU time was computed by averaging the run times of 24 Kodak images. According to the table, the processing time of the proposed method was lower than those of two conventional methods.

Table 2 RMSE comparison of the proposed method and conventional methods (Dmytro Paliy [17] and Tao Ma [19]) on the 24 test images.

	Paliy's method [17]			Ma's method [19]			Proposed		
	R	G	B	R	G	B	R	G	B
1	7.35	5.96	7.49	6.48	6.31	6.39	6.31	6.14	6.18
2	5.68	3.62	4.37	4.78	3.65	3.73	4.80	3.53	3.54
3	4.76	4.00	4.68	4.26	3.92	4.32	3.99	3.55	4.05
4	5.52	4.30	4.92	4.70	3.84	3.90	4.79	3.80	3.86
5	8.03	6.66	8.14	6.74	6.33	6.77	6.57	6.14	6.62
6	7.11	6.16	7.30	6.31	6.19	6.44	5.95	5.90	6.08
7	5.01	3.82	5.36	3.90	3.56	4.07	3.69	3.30	3.85
8	10.04	8.02	9.89	8.84	8.42	8.75	8.41	8.01	8.24
9	4.91	3.78	4.86	3.90	3.68	3.96	3.55	3.33	3.63
10	4.86	3.94	4.83	4.05	3.80	4.10	3.71	3.45	3.75
11	6.27	5.28	6.02	5.53	5.18	5.27	5.30	4.97	5.01
12	4.94	4.02	4.92	4.12	3.86	4.07	3.85	3.55	3.75
13	9.88	9.18	10.50	9.27	9.27	9.76	9.25	9.35	9.69
14	7.71	6.25	7.13	6.69	5.78	6.46	6.80	5.85	6.45
15	7.69	6.51	7.22	6.89	6.03	6.17	6.67	5.79	5.78
16	5.00	4.45	5.10	4.58	4.50	4.62	4.32	4.28	4.35
17	5.42	4.84	5.65	4.75	4.65	4.88	4.73	4.66	4.69
18	7.10	6.32	7.57	6.50	6.17	6.64	6.49	6.15	6.66
19	6.66	5.32	6.24	5.69	5.39	5.29	5.24	4.92	4.88
20	6.86	6.26	7.33	6.42	6.27	6.50	5.45	5.49	5.71
21	6.35	5.49	6.63	5.52	5.45	5.74	5.19	5.16	5.41
22	6.16	5.14	6.29	5.54	4.78	5.23	5.58	4.64	5.15
23	5.08	4.13	5.85	4.74	3.76	4.02	4.37	3.21	3.67
24	8.14	7.51	9.48	7.77	7.46	8.48	7.92	7.59	8.47
avg.	6.52	5.46	6.57	5.75	5.34	5.65	5.54	5.11	5.39

Table 3 Computational complexity for the presented joint methods of deblurring and demosaicing (measured in seconds on an Intel Core2 Quad Q8200 processor).

Method	Paliy's method [17]	Ma's method [19]	Proposed
CPU time (s)	11.63	13.50	1.13

5. Conclusions

In this paper, we have proposed a joint method of deblurring and demosaicing. The proposed method is based on the local edge characteristics because the edge information is necessary to improve the demosaicing and deblurring performance. The edge information is estimated in the Bayer domain by using the proposed projection based edge estimation method. Then, edge adaptive deblurring and edge directional interpolation were processed simultaneously from the estimated edge information. To reduce the computational load, the proposed method was implemented by using a spatial filter of the EACLS. The proposed method was applied to various images to verify the performance of the proposed algorithm. The proposed method improved the overall image quality in both flat and edge regions. The simulation results indicated that the proposed method provided better image quality than conventional approaches in both visual and numerical ways.

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