A Remainder Set Near-Lossless Compression Method for Bayer Color Filter Array Images

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Abstract

In order to improve the compression performance of Bayer CFA images exposed continuously, a new high performance remainder set near-lossless compression method is presented. Based on channel-separated-filtering, several typical Bayer CFA image compression methods are compared with the proposed remainder set algorithm. It is proved that the remainder set algorithm has not only the better compression performance, i.e., the lower bits per pixel (average about 2.16bpp), but also the better reconstructed CFA image PSNR (average about 52.31dB).

Keywords: Color filter array; Demosaicing; Remainder set near-lossless compression; Channel-separated-filtering

1. Introduction

Most digital cameras use a single image sensor to capture scene images. A color filter array is usually coated over a sensor to get only one of the three chromatic components at each pixel location. Bayer pattern CFA [1], as shown in Fig.1, is one format CFA which is used widely for its excellent pixel location arrangement. To get a full color image, Bayer CFA image is interpolated based on the only one chromatic component at each pixel location. This course is defined as demosaicing [10], [14] etc.

Conventional compression methods for Bayer CFA image is demosaicing-first, and then compression is carried out. As [3], [4] show, the compression-first scheme outperforms the conventional demosaicing-first scheme in terms of image quality and complexity. Xiang Xie et al have done much work about Bayer CFA image compression in [4], [6], [7], [11], etc. In these methods, channel-separated-filtering is a key step, and then JPEG or JPEG\_LS is used. In [2], Mallat wavelet packet transform and adaptive Rice code are used to compress CFA image. In [3], a context matching technique is the main approach of the algorithm. However, these compression techniques, including [5], [8], [9], etc., concentrate on how to reduce the redundancy presented in an individual CFA image. This model of compression ignores an additional type of redundancy that exists in CFA images exposed continuously. This type of redundancy in set of similar images, which is named after "set redundancy", was introduced for the first time by
Karadimitriou in [12]. Samy Ait-Aoudia and Abdelhalim Gabis analysed and compared several set redundancy compression methods for medical gray images and satellite gray images in [13]. However, CFA image has its own characteristics. In this paper, a new remainder set near-lossless compression approach is proposed to compress Bayer CFA images exposed continuously.

2. Channel-Separated Inverse Filters

In a full color image, the adjacent pixels in one channel have higher relativity than that between different channels. Sampled from a full color nature image, Bayer CFA data have more high frequency components in horizontal direction and vertical direction, and the relativity between adjacent pixels is decreased, as is disadvantageous to compression. To get high compression performance, filtering is very important in one channel. Because of natural pixels’ randomicity, equiprobable filtering is reasonable. Therefore, suppose inverse filters are \( H_{\text{inv}} \) and \( G_{\text{inv}} \), where \( H_{\text{inv}} \) is the filter and \( G_{\text{inv}} \) is the defilter, and the processed image size is \( M \times N \), then

\[
H_{\text{inv}} = \frac{1}{n^2} \begin{bmatrix}
1 & 1 & \cdots & 1 \\
1 & 1 & \cdots & 1 \\
\vdots & \vdots & \ddots & \vdots \\
1 & 1 & \cdots & 1
\end{bmatrix}, \quad G_{\text{inv}} = \begin{bmatrix}
-1 & -1 & \cdots & -1 \\
-1 & -1 & \cdots & -1 \\
\vdots & \vdots & \ddots & \vdots \\
-1 & -1 & \cdots & -1
\end{bmatrix}
\]  \hspace{1cm} (1)

Where \( n \in \{2, 3, \ldots, \min\{M, N\}\} \).

3. Proposed Remainder Set Compression Algorithm

The proposed remainder set near-lossless compression method for Bayer CFA images consists of two parts, transmitting part and receiving part. Transmitting part obtains CFA images, compresses and transmits them, and receiving part gets and reconstructs them.

In the transmitting part, following steps are included.

- Construct set \( U \)

Construct a set unit \( S \) with \( P_1, P_2, \cdots, P_n \), where \( P_1, P_2, \cdots, P_n \) are \( M \times N \) Bayer CFA images exposed continuously. Then compute minimum image \( I_0 \) and image remainder \( I_k \) following equations (2).

For \( \forall b_k \in P_k, k = 1, 2, \cdots, n \), \( \exists \lambda \), let \( a_{b_k} \), \( a_k \) satisfy equations (2), where \( a_{b_k} \in I_0 \), \( a_k \in I_k \), \( 1 \leq i \leq M/4 \), \( 1 \leq j \leq N/4 \), and \((x, y)\) in \( a_{b_k}(x, y, l) \), \( a_k(x, y, l) \) and \( b_k(x, y, l) \) is pixel position coordinate and \( l \) represents the color channel, i.e. 1, 2, 3 represents R, G, B respectively.
\[ a_i (2i-1, 2j-1, 2) = \min_{(i', j')} \left\{ \arg \left[ \min_{(i', j')} |i' - b_i (x, y, 2)| \right] \right\} \]
\[ a_i (x, y, 2) = b_i (x, y, 2) - a_i (2i-1, 2j-1, 2) \]
\[ \varphi = \{(4i-1, 4j-1), (4i-1, 4j-3), (4i-3, 4j-1), (4i-3, 4j-3)\} \]

\[ a_i (2i, 2j-2) = \min_{(i', j')} \left\{ \arg \left[ \min_{(i', j')} |i' - b_i (x, y, 2)| \right] \right\} \]
\[ a_i (x, y, 2) = b_i (x, y, 2) - a_i (2i, 2j-2) \]
\[ \varphi = \{(4i, 4j), (4i, 4j-2), (4i-2, 4j), (4i-2, 4j-2)\} \]

\[ a_i (2i-1, 2j, 1) = \min_{(i', j')} \left\{ \arg \left[ \min_{(i', j')} |i' - b_i (x, y, 1)| \right] \right\} \]
\[ a_i (x, y, 1) = b_i (x, y, 1) - a_i (2i-1, 2j, 1) \]
\[ \varphi = \{(4i-1, 4j), (4i-1, 4j-2), (4i-3, 4j), (4i-3, 4j-2)\} \]

\[ a_i (2i, 2j-1, 3) = \min_{(i', j')} \left\{ \arg \left[ \min_{(i', j')} |i' - b_i (x, y, 3)| \right] \right\} \]
\[ a_i (x, y, 3) = b_i (x, y, 3) - a_i (2i, 2j-1, 3) \]
\[ \varphi = \{(4i, 4j-1), (4i, 4j-3), (4i-2, 4j-1), (4i-2, 4j-3)\} \]

\[ I_0 \text{ and } I_1 \text{ form set } U, \text{ i.e. } U = \{I_k, k = 0, 1, 2, \ldots, n\}. \]

**Channel separated**

A CFA image is sampled from a natural image. High frequency components are produced and the relativity between adjacent pixels is decreased. Therefore, low pass filtering is needed before compression. The values of the adjacent pixels in one channel are more similar than those of the pixels in the same coordinate in different channels. This means that the relativity in one channel is higher than that between different channels. Hence, channel-separated-filtering is used here. Sample Bayer CFA image remainder \( I_k, k \neq 0 \) by equations (3) to separate it into three mesh images, i.e. \( I_{k, R}(x, y), I_{k, G}(x, y) \) and \( I_{k, B}(x, y) \), where \( 1 \leq x \leq M, 1 \leq y \leq N \).

\[ I_{k, R}(x, y) = I_k (x, y) \times \sum_{i=1}^{M/2} \sum_{j=1}^{N/2} \delta(x - 2i + 1, y - 2j) \]
\[ I_{k, G}(x, y) = I_k (x, y) \times \sum_{i=1}^{M/2} \sum_{j=1}^{N/2} [\delta(x - 2i + 1, y - 2j + 1) + \delta(x - 2i, y - 2j)] \]
\[ I_{k, B}(x, y) = I_k (x, y) \times \sum_{i=1}^{M/2} \sum_{j=1}^{N/2} \delta(x - 2i, y - 2j + 1) \]

Following equations (4), project \( I_{k, R}(x, y), I_{k, G}(x, y) \) and \( I_{k, B}(x, y) \) to \( I_k, R_2(x, y), I_k, G_2(x, y) \) and \( I_k, B_2(x, y) \) respectively. This makes channel-separated images from mesh to rectangle.

\[ a_{R, 2} (x, y) = a_{R, 2} (i, j) = a_{R, 2} (2i-1, 2j), 1 \leq x \leq M/2, 1 \leq y \leq N/2 \]
\[ a_{G, 2} (x, y) = \begin{cases} a_{G, 2} (2i-1, j) = a_{G, 2} (2i-1, 2j-1) & , 1 \leq x \leq M, 1 \leq y \leq N/2 \\ a_{G, 2} (2i, j) = a_{G, 2} (2i, 2j) & \\ \end{cases} \]
\[ a_{B, 2} (x, y) = a_{B, 2} (i, j) = a_{B, 2} (2i, 2j-1), 1 \leq x \leq M/2, 1 \leq y \leq N/2 \]

Where \( 1 \leq i \leq M/2, 1 \leq j \leq N/2, a_{R, 2} \in I_k, R_2, a_{G, 2} \in I_k, G_2, a_{B, 2} \in I_k, B_2 \).
Filtering

Suppose $I_{k, s3}(x, y)$, $I_{k, g3}(x, y)$ and $I_{k, b3}(x, y)$ are channel-separated-filtered images, then

$$
\begin{align*}
I_{k, s3}(x, y) &= I_{k, s2}(x, y) * H, \quad 1 \leq x < M/2, 1 \leq y < N/2 \\
I_{k, s3}(x, N/2) &= I_{k, s2}(x, N/2) * H^r, \quad 1 \leq x < M/2 \\
I_{k, s3}(M/2, y) &= I_{k, s2}(M/2, y) * H^r, \quad 1 \leq y < N/2 \\
a_{k, s3}(M/2, N/2) &= a_{k, s2}(M/2, N/2) \\
I_{k, g3}(x, y) &= I_{k, g2}(x, y) * H, \quad 1 \leq x < M, 1 \leq y < N/2 \\
I_{k, g3}(x, N/2) &= I_{k, g2}(x, N/2) * H^r, \quad 1 \leq x < M \\
I_{k, g3}(M, y) &= I_{k, g2}(M, y) * H^r, \quad 1 \leq y < N/2 \\
a_{k, g3}(M, N/2) &= a_{k, g2}(M, N/2)
\end{align*}
$$

(5)

Where ‘ * ’ means convolution operation, and $H = \frac{1}{4}\begin{bmatrix}1 & 1 \\ 1 & 1 \end{bmatrix}$, $H^r = \frac{1}{2}\begin{bmatrix}1 \\ 1 \end{bmatrix}$, $H^g = \frac{1}{2}\begin{bmatrix}1 \\ 1 \end{bmatrix}$, $a_{k, s3} \in I_{k, s3}$, $a_{k, g3} \in I_{k, g3}$, $a_{k, b3} \in I_{k, b3}$, $S \in \{R, B\}$. The filtering starts from the left-top pixel of the channel-separated rectangular image data in a raster-scan manner.

Compression and transmission

Because the reconstructed CFA image data will be the basement of demosaicing, the precision of the reconstructed pixel value is very important. Portable Network Graphic Format (PNG) is based on LZ77 derived algorithm and Human codec, and it is a real lossless compression algorithm and adapts to CFA image compression well. Therefore, PNG is used in our proposed method. The minimum image $I_0$ is compressed by PNG directly, and the remainder image $I_k$ is filtered by channel-separated method and then compressed by PNG. The size of $I_0$ is a quarter of $I_k$. Suppose $I_{k4}$ is compressed from $I_0$, and $I_{k, s4}(x, y)$, $I_{k, g4}(x, y)$ and $I_{k, b4}(x, y)$ is compressed from $I_{k, s3}(x, y)$, $I_{k, g3}(x, y)$ and $I_{k, b3}(x, y)$ respectively. $I_{k4}$, $I_{k, s4}(x, y)$, $I_{k, g4}(x, y)$ and $I_{k, b4}(x, y)$ are transmitted together. The whole transmitting part of the proposed method is shown in Fig.2.

In the receiving part, the proposed method includes following steps.

Decompression and defiltering

Decompress the received image $I_{k4}$, $I_{k, s4}(x, y)$, $I_{k, g4}(x, y)$ and $I_{k, b4}(x, y)$ by PNG decoder, and get decompressed image $I_{k, s4}(x, y)$, $I_{k, g4}(x, y)$ and $I_{k, b4}(x, y)$. Then the defiltering starts from the right-bottom corner of the decompressed image in a deraster-scan manner. For each image, the first pixel on the right-bottom corner is not filtered. The last row is filtered by $G_y$ and the last column is filtered by $G_x$. The other pixels are defiltered by $G$, row by row following the deraster-scan manner. Suppose $I_{k, b2}(x, y)$, $I_{k, g2}(x, y)$ and $I_{k, s2}(x, y)$ are the defiltered images, then
\[
\begin{align*}
\{a_{k_{52}, rc}(M/2,N/2) = a_{k_{51}, rc}(M/2,N/2) & \\
I_{k_{52}, rc}(M/2,y) = I_{k_{53}, rc}(M/2,y) & \cdot G_H^T, \quad 1 \leq y < N/2 \\
I_{k_{52}, rc}(x,N/2) = I_{k_{53}, rc}(x,N/2) & \cdot G_H^T, \quad 1 \leq x < M/2 \\
I_{k_{52}, rc}(x,y) = I_{k_{53}, rc}(x,y) & \cdot G, \quad 1 \leq x < M/2, 1 \leq y < N/2 \\
a_{k_{52}, rc}(M/2, y) = a_{k_{53}, rc}(M, N/2) & \\
I_{k_{52}, G2, rc}(M,y) = I_{k_{53}, G3, rc}(M,y) & \cdot G_H^T, \quad 1 \leq y < N/2 \\
I_{k_{52}, G2, rc}(x, N/2) = I_{k_{53}, G3, rc}(x, N/2) & \cdot G_H^T, \quad 1 \leq x < M \\
I_{k_{52}, G2, rc}(x, y) = I_{k_{53}, G3, rc}(x, y) & \cdot G, \quad 1 \leq x < M, 1 \leq y < N/2
\end{align*}
\]

Where ‘*’ means convolution operation, and \(G = \begin{bmatrix} 4 & -1 \\ -1 & -1 \end{bmatrix}\), \(G_H^T = \begin{bmatrix} 2 & -1 \\ -1 & -1 \end{bmatrix}\), \(a_{k_{53}, rc} \in I_{k_{53}, rc}\), \(a_{k_{53}, G1, rc} \in I_{k_{53}, G1, rc}\), \(a_{k_{53}, G2, rc} \in I_{k_{53}, G2, rc}\), \(S \in \{R, B\}\).

- **Reconstruct remainders and get set \(U_{rc}\)**

\(I_{k_{52}, rc}(x, y), I_{k_{53}, rc}(x, y)\) and \(I_{k_{52}, rc}(x, y)\) are 3 rectangular gray images. Project them to mesh images, \(I_{k_{51}, rc}(x, y), I_{k_{51}, G1, rc}(x, y)\) and \(I_{k_{51}, G1, rc}(x, y)\), following equations (7).

\[
\begin{align*}
a_{k_{51}, rc}(2x-1, 2y) = a_{k_{51}, rc}(x, y), & \quad 1 \leq x \leq M/2, 1 \leq y \leq N/2 \\
a_{k_{51}, G1, rc}(2x-1, 2y-1) = a_{k_{51}, G2, rc}(2x-1, y), & \quad 1 \leq x \leq M/2, 1 \leq y \leq N/2 \\
a_{k_{51}, G1, rc}(2x, 2y) = a_{k_{51}, G2, rc}(2x, y), & \quad 1 \leq x \leq M/2, 1 \leq y \leq N/2 \\
a_{k_{51}, rc}(2x, 2y) = a_{k_{51}, rc}(x, y), & \quad 1 \leq x \leq M/2, 1 \leq y \leq N/2
\end{align*}
\]

Where \(a_{k_{51}, rc} \in I_{k_{51}, rc}\), \(a_{k_{51}, G1, rc} \in I_{k_{51}, G1, rc}\), \(a_{k_{51}, G2, rc} \in I_{k_{51}, G2, rc}\), \(a_{k_{51}, B1, rc} \in I_{k_{51}, B1, rc}\), \(a_{k_{52}, B1, rc} \in I_{k_{52}, B1, rc}\). Reconstruct CFA image remainder \(I_{k_{51}, rc}\) following equation (8).

\[
I_{k_{51}, rc} = I_{k_{51}, B1, rc} \cup I_{k_{51}, G1, rc} \cup I_{k_{51}, B1, rc}
\]

Then the reconstructed set \(U_{rc}\) is \(\{I_{k_{51}, rc}, k = 0, 1, 2, \ldots, n\}\).

- **Reconstruct CFA images**

To reconstruct CFA images from the remainders is the reverse processing course of equations (2). Based on equations (2), it is easy to get equations (9) and reconstruct CFA image \(P_{rc}\). Then we can get the reconstructed CFA image set unit \(S_{rc} = \{P_{rc}, P_{rc}, \ldots, P_{rc}\}\).

\[
\begin{align*}
h_{rc}(x, y, 2) & = a_{rc}(x, y, 2) + a_{rc}(2i-1, 2j-1, 2) \\
\varphi & = \{(4i-4, j-1),(4i-4, j-3),(4i-3, j-1),(4i-3, j-3)\} \\
h_{rc}(x, y, 2) & = a_{rc}(x, y, 2) + a_{rc}(2i, 2j, 2) \\
\varphi & = \{(4i, 4j),(4i, 4j-2),(4i-2, 4j),(4i-2, 4j-2)\} \\
h_{rc}(x, y, 1) & = a_{rc}(x, y, 1) + a_{rc}(2i-1, 2j, 1) \\
\varphi & = \{(4i-1, 4j),(4i-1, 4j-2),(4i-3, 4j),(4i-3, 4j-2)\} \\
h_{rc}(x, y, 3) & = a_{rc}(x, y, 3) + a_{rc}(2i, 2j-1, 3) \\
\varphi & = \{(4i, 4j-1),(4i, 4j-3),(4i-2, 4j-1),(4i-2, 4j-3)\}
\end{align*}
\]

Where \(h_{rc} \in P_{rc}\), \(a_{rc} \in I_{rc}\), \(a_{rc} \in I_{rc}\), \(1 \leq i \leq M/4\) and \(1 \leq j \leq N/4\). The whole receiving part of the proposed method is shown in Fig.3.
4. Results

We expose a moving object continuously and get nine $2048 \times 1536$ images as Fig.4a. Sample Fig.4a and get Bayer CFA images as Fig.4b, which are used as the original test images, i.e. $S = \{ P_1, P_2, \ldots, P_9 \}$. Following our proposed method in part III, compress the images, transmit, decompress and reconstruct. We can get $S_{\text{rec}} = \{ P_{1, \text{rec}}, P_{2, \text{rec}}, \ldots, P_{9, \text{rec}} \}$, as Fig.4c.
Because channel-separated-filtering is a vital step for good compression performance, Bayer CFA images exposed continuously are filtered in a channel-separated manner firstly. Based on that, suppose JPEG is method one, the algorithm in [2] is method two, the algorithm in [3] is method three and PNG is method four. Then method one, method two, method three and method four are used to compress the object images in Fig.4b. Table 1 gives achieved bit-rates of various compression algorithms in terms of bits per pixel (bpp) based on channel-separated-filtering, where $n$ means the exposed number continuously. In Table 1, the bit-rate of our proposed method is much lower than that of method one, method two, method three and method four. Ours gets rid of the redundancy between CFA images exposed continuously, so it has better compression performance. On average, the proposed method achieves a bit-rate of 2.16 bpp which is around 0.28, 1.21, 0.91 and 0.19 bpp lower than that achieved by method one, two, three and four respectively.

Table 2 reveals the average PSNRs of the CFA images reconstructed by various compression methods based on channel-separated-filtering. Ours has the best PSNR, and the average is about 52.31 dB. Method two, three and four have the same PSNR value, because they are all lossless compression approaches except losing PSNR during channel-separated-filtering. Ours keeps $I_o$ lossless compressed without filtered, and therefore the reconstructed CFA images have better average PSNR. The average PSNR of our method is about 1.02 dB higher than that of method two, method three or method four, and about 4.19 dB higher than that of method one.

Table 1. Achieved bit-rates (bpp) of various compression methods

| n  | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|----|-----|-----|-----|-----|-----|-----|-----|-----|
| Method 1 | 2.4115 | 2.4210 | 2.4329 | 2.4329 | 2.4479 | 2.4528 | 2.4570 | 2.4609 |
| Method 2 | 3.3631 | 3.3623 | 3.3663 | 3.3663 | 3.3652 | 3.3773 | 3.3749 | 3.3720 |
| Method 3 | 3.0712 | 3.0747 | 3.0786 | 3.0786 | 3.0778 | 3.0825 | 3.0831 | 3.0795 |
| Method 4 | 2.3320 | 2.3411 | 2.3496 | 2.3496 | 2.3594 | 2.3624 | 2.3649 | 2.3669 |
| Ours    | 2.0347 | 2.1002 | 2.1342 | 2.1342 | 2.1913 | 2.2101 | 2.2282 | 2.2410 |

Table 2. Average PSNRs (dB) of various compression methods

| n  | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|----|-----|-----|-----|-----|-----|-----|-----|-----|
| Method 1 | 48.1858 | 48.1613 | 48.1404 | 48.1255 | 48.1115 | 48.1014 | 48.0899 | 48.0824 |
| Method 2 | 51.3324 | 51.3198 | 51.3067 | 51.2913 | 51.2811 | 51.2738 | 51.2652 | 51.2601 |
| Method 3 | 51.3324 | 51.3198 | 51.3067 | 51.2913 | 51.2811 | 51.2738 | 51.2652 | 51.2601 |
| Method 4 | 51.3324 | 51.3198 | 51.3067 | 51.2913 | 51.2811 | 51.2738 | 51.2652 | 51.2601 |
| Ours    | 53.2125 | 52.6735 | 52.4285 | 52.2691 | 52.1193 | 52.0144 | 51.9282 | 51.8617 |

Based on Table 1 and Table 2, the curves of bit-rates, average PSNRs are shown in Fig.5a and Fig.5b respectively. In Fig.5, it is evident that our method has lower bit-rate and the higher PSNR.
5. Conclusion

In this paper, a remainder set near-lossless compression method for Bayer CFA images exposed continuously is presented. In the method, channel-separated-filtering is a key step. To construct the minimum image in the selected CFA images is another key step. Based on channel-separated-filtering, several other typical CFA image compression methods are compared with our remainder set method. Obviously, the results show that our method has better compression performance and better PSNR.

![Fig.5. Performance comparison of various compression methods](image_url)

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