Proceedings of 2009 APSIPA Annual Summit and Conference, Sapporo, Japan, October 4-7, 2009

A Fast Reversible Compression Algorithm for Bayer Color Filter Array Images

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Abstract *– Most digital cameras perform color demosaicing and compression sequentially to yield a color output. Recent reports indicate that the alternative compression-then-demosaicing approach outperforms the demosaicing-then-compression approach in terms of image quality and complexity. This paper presents a fast reversible Bayer image compression algorithm for the alternative approach. A statistic-based prediction is proposed to de-correlate the wavelet subband coefficients. By learning from experiences, the proposed predictor can improve its prediction performance adaptively. A context-based Golomb Rice code is then proposed to compress the subband residues. Simulation results show that, as compared with the existing lossless CFA image coding methods, the proposed algorithm can achieve a low bit-rate with lesser computation.*

1. INTRODUCTION

To reduce cost, most digital cameras acquire scenes using a single image sensor. In these cameras, a Bayer color filter array (CFA) [1], as shown in Fig. 1, is placed in front of the sensor such that the sensor samples only one of the three primary color components at each pixel. The mosaic-like CFA image, i.e. the raw sensor output, is first converted to a full color image, via color demosaicing [2-5], and then compressed for transmission or for storage.

Recently, some reports [2,3] pointed out that such a demosaicing-then-compression approach is inefficient in a compression point of view as the demosaicing process introduces the redundancy which will be eventually removed in the later compression step. Accordingly, an alternative approach [2,4] which carries out compression prior to demosaicing has been proposed lately.

Under this new workflow, a digital camera can have a higher quality color output and more power-efficient design as the critical yet computationally heavy processing steps like color demosaicing and post-processing can be carried out offline in a powerful personal computer. These advantages motivate the demand of compression techniques for CFA images.

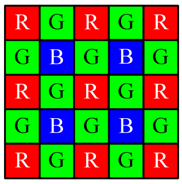


Fig. 1 – Bayer pattern having a center at red sampling position

Generally, CFA image compression can be either lossy or lossless. Lossy compression results in a decompressed output different from the original [2,4-6]. It is rarely used in practice as the demosaicing to be carried out in the future is very sensitive to the corruption introduced in the compression. Lossless compression, on the contrary, provides a decompressed output exactly the same as the original. It is commonly used for some high-end photography applications like professional advertising where the original CFA image is required for producing the high quality full color image.

Obviously, some lossless compression standards for grayscale images such as JPEG-LS [7] and JPEG 2000 [8] can be directly applied to compress CFA images. Nevertheless, they attain a fair compression performance only. Recently, two advanced lossless CFA image compression algorithms [9,10] were proposed. In [9] (LCMI), the Mallat packet transform is exploited to de-correlate the mosaic color data. The transform coefficients are then compressed by adaptive Golomb Rice code. As for CMBC[10], it uses a context matching technique to rank the neighboring pixels for predicting a pixel. This method generally provides a better compression performance as compared with the existing lossless CFA image compression schemes. However, it demands a relatively high computational complexity.

In [9], it is found that applying a simple one-level 2D-wavelet transform to a mosaic CFA image is equivalent to separately transforming the full resolution green channel and the down sampled color difference images and then summing up the results. Based on this

(a) (b)

Fig. 2 – (a) A mosaic CFA image and (b) its one-level 5/3 wavelet transform outputs: *LL* (top-left), *LH* (top-right), *HL* (bottom-left), *HH* (bottom-right) subbands

finding a fast reversible compression algorithm for CFA images is proposed in this paper. This algorithm uses a statistic-based prediction technique to de-correlate the subband coefficients. In particular, the statistics about the relative position between a given coefficient and its connected neighbor whose value is closest to that of the given coefficient is collected to adaptively improve the prediction performance. The prediction residues are then entropy coded with the proposed context-based Golomb Rice code. Simulation results show that the proposed compression method outperforms most lossless compression schemes and provides a good compression performance at a lower computation cost.

This paper is organized as follows. In Section II, the statistic-based prediction for subband coefficients is presented. In Section III, the structure of the proposed compression algorithm is described. In Section IV, some simulation results are demonstrated. Finally, in Section V, a brief conclusion is provided.

2. STATISTIC-BASED PREDICTION

A one-level 2-D wavelet transform can convert the mosaic CFA data into four smooth subbands as shown in Fig. 2. Based on the property of each subband, a simple adaptive prediction technique is proposed in this section to de-correlate the subband coefficients.

The proposed compression method separately handles the subbands in a raster scan order. Assume that we are now processing a particular coefficient denoted as c_0 in a particular subband. The value of coefficient c_0 can be predicted as

$$\hat{c}_0 = \sum_{k=1,2,3,4} w_k c_k \tag{1}$$

where c_k for $k = 1, 2, 3$ and 4 are c_0's causal neighbors as shown in Fig. 3 and w_k is the weight for c_k. The weights are normalized such that $w_1 + w_2 + w_3 + w_4 = 1$.

We note that only coefficients c_k for $k = 1, 2, 3$ and 4 are considered for the prediction because they are the four causal coefficients closest to c_0 in distance. These coefficients provide a higher correlation to c_0 and are available when decoding c_0.

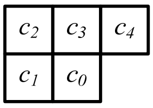
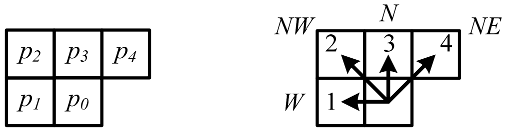


Fig. 3 – A current subband coefficient c_0 and its causal adjacent neighbors for the proposed statistic-based prediction



(a) (b)

Fig. 4 – (a) A causal template and (b) four possible optimal direction indexes for coefficient p_0

To compute the weight w_k, the optimal neighbor of coefficient c_k is determined first. The optimal neighbor of any particular coefficient p_0 in the subband being processed, say p_0^*, is defined as

$$p_0^* = \arg\min_{p_i} |p_i - p_0| \quad \text{for } i=1,2,3,4. \tag{2}$$

where p_i for i=1,2,3,4 are p_0's neighbors in the causal template shown in Fig. 4a. When there are more than one optimal neighbors, one of them is randomly selected.

The optimal neighbor of p_0 can be p_0's western, northwestern, northern or northeastern neighbor. The four directions are indexed as shown in Fig.4b. For reference, the direction from coefficient p_0 to its optimal neighbor p_0^* is referred to as the optimal direction of p_0 and its corresponding index value is denoted as d_{p_0} hereafter.

In the course of prediction, the optimal neighbors of all processed coefficients in the subband can be determined. Accordingly, when processing the current processing coefficient c_0 shown in Fig.3, the weight for predicting the current processing coefficient c_0 can be determined as

$$w_k = Prob(d_{c_0} = k \mid d_{c_1}, d_{c_2}, d_{c_3}, d_{c_4}) \quad \text{for } k=1,2,3,4 \tag{3}$$

where d_{c_j} is the index value of the optimal direction of coefficient c_j. $Prob(d_{c_0} = k \mid d_{c_1}, d_{c_2}, d_{c_3}, d_{c_4})$ is the probability that the optimal direction index of c_0 is k under the condition that d_{c_1}, d_{c_2}, d_{c_3} and d_{c_4} are known.

Since d_{c_0} and hence $Prob(d_{c_0} = k \mid d_{c_1}, d_{c_2}, d_{c_3}, d_{c_4})$ are not available during decoding, to predict the current coefficient c_0 in the proposed method, the probability is estimated as

$$Prob(d_{c_0} = k \mid d_{c_1} d_{c_2} d_{c_3} d_{c_4}) = \frac{C(k \mid d_{c_1}, d_{c_2}, d_{c_3}, d_{c_4})}{\sum_{j=1,2,3,4} C(j \mid d_{c_1}, d_{c_2}, d_{c_3}, d_{c_4})} \quad \text{for } k=1,2,3,4 \tag{4}$$

where C(•|•) is a conditional counter used to keep track of the occurrence frequency of that k is the optimal direction index of a processed coefficient whose western, northwestern, northern and northeastern neighbors' optimal direction indices are, respectively, d_{c_1}, d_{c_2}, d_{c_3} and d_{c_4}.

As we have $d_{c_j} \in \{1,2,3,4\}$ for j=1,2,3,4, there are totally 256 (=4^4) possible combinations of d_{c_1}, d_{c_2}, d_{c_3} and d_{c_4}. Accordingly, 256×4 counters are required and a table of 256×4 entries is constructed to maintain these counters. This table is initialized with all entries set to 1 before the compression starts and is updated in the course of the compression. As soon as coefficient c_0 is encoded, counter $C(d_{c_0} \mid d_{c_1}, d_{c_2}, d_{c_3}, d_{c_4})$ is increased by 1 to update the table.

With the table which collects the statistics so far about the occurrence frequencies of particular optimal direction index values when processing the subband, the proposed predictor can learn from experiences to improve its prediction performance adaptively.

3. PROPOSED COMPRESSION ALGORITHM

Fig. 5 shows the structure of the proposed compression algorithm. In the encoding phase, the input CFA image is first converted to four subbands, namely *LL*, *LH*, *HL* and *HH*, by applying a simple one-level reversible 5/3 wavelet transform [10]. The subbands are then coded separately.

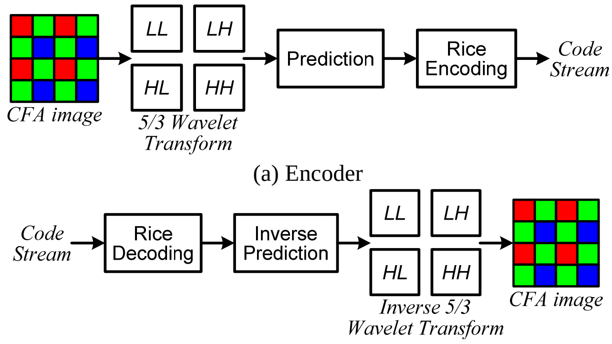
To code a subband, the subband is raster-scanned and each subband coefficient is predicted with its four causal neighboring coefficients by using statistic-based prediction, the prediction technique proposed in Section 2. The prediction error of the subband coefficient, say $e_{i,j}$, is then given by

$$e_{i,j} = c_{i,j} - \hat{c}_{i,j} \quad (5)$$

where $c_{i,j}$ is the real coefficient value and $\hat{c}_{i,j}$ is the predicted value of $c_{i,j}$. The error residue $e_{i,j}$ is then mapped to a non-negative integer as follows to reshape its value distribution from a Laplacian one to an exponential one for Rice code.

$$E_{i,j} = \begin{cases} 2e_{i,j} & \text{if } e_{i,j} \geq 0 \\ -2e_{i,j} - 1 & \text{otherwise} \end{cases} \quad (6)$$

The Rice code is employed in the proposed compression method because of its simplicity and its efficiency in handling exponentially distributed sources. In Rice code, the mapped residue $E_{i,j}$ is compressed by splitting it into a quotient Q=floor($E_{i,j}/\lambda$) and a remainder R=$E_{i,j}$modλ with a positive integer $\lambda=2^k$ called Rice parameter, where $k\geq 0$. The quotient and the remainder are then saved for storage or transmission.



(a) Encoder

(b) Decoder

Fig. 5 – Structure of the proposed compression algorithm

Parameter k is critical to the compression performance as it determines the code length of $E_{i,j}$. For a geometric source $\boldsymbol{S}$ with distribution parameter $\rho \in (0,1)$ (i.e. Prob($\boldsymbol{S}$=s)=$(1-\rho)\rho^s$ for s=0,1,2,…), the optimal coding parameter k is given as

$$k = \max\left\{0, ceil\left(\log_2\left(\frac{\log\phi}{\log\rho^{-1}}\right)\right)\right\} \text{ and } \rho = \frac{\mu}{1-\mu} \quad (7)$$

where $\phi = (\sqrt{5}+1)/2$ is the golden ratio [11] and μ is the expectation value of the source. As long as μ is known, parameter ρ and hence the optimal coding parameter k for the whole source can be determined easily.

In the proposed method, μ is adaptively estimated in the course of encoding a subband. In particular, it is estimated by

$$\tilde{\mu} = round\left(\frac{\alpha\tilde{\mu}_p + M_{i,j}}{1+\alpha}\right) \text{ and } M_{i,j} = \frac{1}{4}\sum_{(m,n)\in\left\{\substack{(i-1,j),(i-1,j-1),\\(i-1,j+1),(i,j-1)}\right\}} E_{m,n} \quad (8)$$

where $\tilde{\mu}$ is the current estimate of μ for selecting the k to determine the codeword format of the current $E_{i,j}$, $\tilde{\mu}_p$ is the previous estimate of $\tilde{\mu}$, $M_{i,j}$ is the local mean of $E_{i,j}$ obtained from the causal adjacent mapped errors, and α is a weighting factor which specifies the significance of $\tilde{\mu}_p$ and $M_{i,j}$ when updating $\tilde{\mu}$. $\tilde{\mu}$ is updated for each $E_{i,j}$.

The initial value of $\tilde{\mu}_p$ is 0 for all subband residue planes, while the value of α is obtained empirically in this paper. Experimental results showed that α=1 can provide a good compression performance.

The decoding process is just the reserve process of encoding. Rice decoding and inverse prediction are applied sequentially to obtain the four wavelet subbands. These subbands are then backward transformed to reproduce the original CFA image.

4. SIMULATION RESULTS

Simulations were carried out to evaluate the compression performance of the proposed method. Twelve 24-bit color images of size 512×768 each as shown in Fig. 6 were sub-sampled according to Bayer pattern to form a set of testing CFA images. These CFA image were then directly coded by the proposed compression algorithm and some representative lossless compression schemes such as JPEG-LS [7], JPEG 2000 (lossless mode) [8], LCMI [9] and CMBC [10].

Table 1 tabulates the output bit-rates of the CFA images achieved by various algorithms. It shows that the proposed scheme outperforms most evaluated methods. On average, the proposed scheme yields a bit-rate as low as 4.885bpp. It is around 1.336, 0.296 and 0.160 bpp lower than those achieved by JPEG-LS, JPEG2000 and LCMI respectively. These results demonstrate that the proposed prediction scheme is robust to remove the CFA data dependency.

As for the computational complexity, the proposed algorithm requires about 0.061s to process a 512×768 CFA image on a 3.0GHz Pentium 4 PC with 1024MB RAM. It is around 0.039s and 0.005s faster than CMBC and LCMI respectively. These results reveal that the proposed compression algorithm is more suitable than CMBC in applications where complexity is the critical concern although its output bit rate is a little bit higher than CMBC.

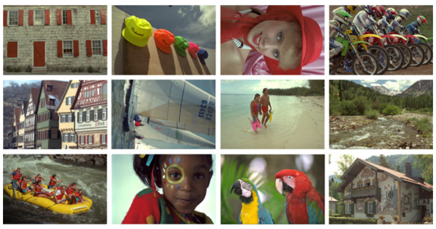


Fig. 6 –Twelve digital color images (referred to as image 1 to image 12 in raster scan order)

Image	JPEG-LS	JPEG 2000	LCMI	CMBC	Ours
1	6.403	5.816	5.824	5.478	5.613
2	5.881	4.216	3.965	3.746	3.882
3	6.682	4.931	4.606	4.379	4.515
4	6.470	5.947	5.859	5.409	5.586
5	6.295	5.899	5.966	5.570	5.716
6	5.395	4.556	4.415	4.227	4.377
7	5.628	4.485	4.307	4.089	4.228
8	6.747	6.372	6.503	6.138	6.188
9	6.288	5.555	5.487	5.171	5.261
10	6.317	4.656	4.396	4.102	4.312
11	6.827	4.525	3.960	3.847	3.937
12	5.719	5.223	5.257	4.873	5.010
Avg.	**6.221**	**5.182**	**5.045**	**4.753**	**4.885**

Table 1 – Achieved bit-rates of various lossless compression algorithms in terms of bits per pixel (bpp)

5. CONCLUSIONS

In this paper, a simple statistic-based prediction lossless compression algorithm for Bayer CFA images is proposed. By learning from previous statistics, the proposed predictor can improve its prediction performance adaptively. A context-based Golomb Rice code is also proposed to compress the subband prediction residues. Experimental results show that the proposed compression scheme can efficiently de-correlate the data dependency at a low complexity cost.

6. ACKNOWLEDGEMENT

This work was supported by the RGC of Hong Kong Special Administrative Region (PolyU5123/08E) and Centre for Multimedia Signal Processing, The Hong Kong Polytechnic University.

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