An efficient prediction-based lossless compression scheme for bayer CFA

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Abstract— In most digital cameras, Bayer Color Filter Array (CFA) images are captured and demosaicing is generally carried out before compression. Recently, it was found that compression-first schemes outperform the conventional demosaicing-first schemes in terms of output image quality. Under this new strategy, digital cameras can have a simpler design and lower power consumption as computationally heavy processes like demosaicing can be carried out in an offline powerful personal computer. An efficient prediction-based lossless compression scheme for bayer CFA image is proposed. It exploits a context matching technique to rank the neighboring pixels when predicting a pixel, an adaptive color difference estimation scheme to remove the color spectral redundancy when handling red and blue samples, and an adaptive Rice coding technique for encoding the prediction residues. Experimental results show that the proposed compression scheme can effectively and efficiently reduce the redundancy in both spatial and color spectral domains. As compared with the existing lossless CFA image coding schemes, the proposed scheme provides the best compression performance.

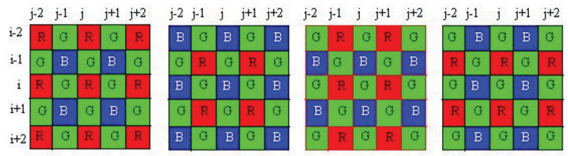
Keywords— Bayer Color Filter Array; adaptive color difference estimation scheme; Rice coding technique

I. INTRODUCTION

Digital imaging devices have become popular over the traditional film cameras and have been widely embedded in consumer electronics ranging from the conventional digital cameras, to pocket devices, to mobile phones, and imaging devices for automotive and surveillance applications. It is therefore not a surprise that digital capturing capabilities are required today also in a wide range of applications, such as computer vision, medical imaging, astronomy, etc.

To capture the image scene, digital cameras use image sensors, usually Charge Coupled Devices (CCD) or Complementary Metal Oxide Semiconductor (CMOS) sensors. Following the trichromatic theory of color vision, an arbitrary color is matched by superimposing appropriate amounts of three-primary colors i.e., Red (R), Green (G) and Blue (B). Since sensor is a monochromatic device, professional digital cameras acquire color information using three sensors with Red (R), Green (G) and Blue (B) color filters having different spectral transmittances.

It is known that the sensor is usually the most expensive component of the digital camera taking from 10% to 25% of the total cost of the device. Therefore, digital camera manufacturers reduce cost and complexity using a single CCD or CMOS sensor with a color filter array. Using this hardware solution, each pixel of the raw, CFA image has its own spectrally selective filter. The specific arrangements of color filters in the CFA vary between the camera manufacturers which use not only RGB CFAs, however, the patterns with complementary Cyan (C), Magenta (M), Yellow (Y) colors, or four-color CFAs formed through mixed primary (RGB) and complementary (CMY) colors or the color primaries and the fourth – spectrally shifted color are in the use as well. Among these, the Bayer pattern [1] (see figure-1.1) is commonly used due to simplicity of the subsequent processing steps. This pattern contains twice as many G components compared to R or B components reflecting the fact that the spectral response of G filters is close to the luminance response of human visual system. Since each color pixel of the Bayer CFA image contains only a single measurement, the two missing color components must be estimated from the adjacent pixels. This process is called CFA demosaicing [2, 3, 4] and is an integral element in single-sensor imaging. Depending on the demosaicing algorithm employed, the cost of the device as well as the quality of the output can vary significantly.



1.1 a 1.1 b 1.1 c 1.1 d

Figure 1.1: Four 5x5 regions of Bayer CFA pattern having their centers at a. red, b. blue, and c&d. green CFA samples

With limited storage space and processing power in digital camera, image data compression is a key component for digital cameras design. In general, a CFA image is first interpolated via a demosaicing process to form a full color image before being compressed for storage. Figure 1.2a shows the workflow of this imaging chain.

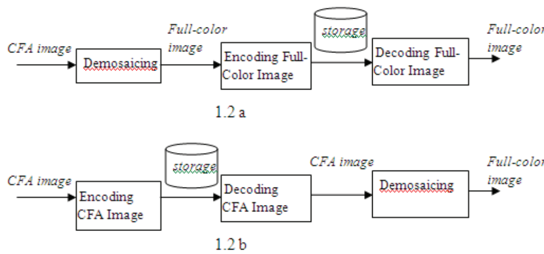


Figure 1.2: Single-sensor camera imaging chain: a. the demosaicing - first scheme and b. the compression - first scheme

Some reports [5, 6] indicated that such a demosaicing-first scheme was inefficient in a way that the demosaicing process always introduced some redundancy which should eventually be removed in the following compression step.

As a result, an alternative processing sequence which carries out compression before demosaicing as shown in figure 1.2b is used in this work.

II. Image Compression Techniques

A. *CFA Image compression Scheme*

Image compression has been becoming increasingly important with the development of aviation, communications, internet and space techniques; especially lossless compression becomes indispensable when there is no loss of information is tolerable such as medical image, remote sensing, image archiving, and satellite communications and so on. Compression ratio and bit distortion always contradict each other, so the techniques pursuing for higher compression ratio with less distortion even without information loss has been one of the popular research issues in image compression.

Out of the two approaches, i.e., demosaicing first and compression first schemes, demosaicing-first processing sequence was inefficient in a way that the demosaicing process always introduced some redundancy which should eventually be removed in the following compression step. As a result, an alternative processing sequence which carries out compression before demosaicing has been proposed. Under this new strategy, digital cameras can have a simpler design and lower power consumption as computationally heavy processes like demosaicing can be carried out in an offline powerful personal computer. This motivates the demand of CFA image compression schemes.

Image data compression is an important component of digital camera design and digital photography. It is more than just an issue of storage and bandwidth, but rather to be considered in light of overall system performance and functionality, particularly in relation to color demosaicing.

In the proposed work, a full color RGB image is sampled according to Bayer pattern in the process of converting it to Bayer CFA image. This CFA image is compressed by using prediction based compression scheme and can be stored. This new design allows lossless compression of color filter array data. Moreover the compression performance results of proposed technique are compared with existing lossless CFA compression techniques.

In brief, objective of this paper is

- To convert full color RGB image to Bayer CFA image.
- To compress the CFA image by using prediction based lossless compression scheme.

- To compare experimental results with existing techniques

B. Lossesless Compression Schemes

There are two categories of CFA image compression schemes: lossy and lossless. Lossy schemes compress a CFA image by discarding its visually redundant information. These schemes usually yield a higher compression ratio. Lossless schemes compress a CFA image without data redundancy but, compression ratio is lower compared to lossy schemes.

Various existing lossless compression schemes such as JPEG2000 (Joint Photographic Experts Group), JPEG-LS (Joint Photographic Experts Group - Lossless) and LCMI (Lossless Compression of Color Mosaic Images) are discussed in detail in this paper. This paper also presents the comparison between these lossless CFA compression schemes.

To get a CFA image, a true color RGB image is to be sub sampled according to Bayer CFA pattern. Prediction based lossless compression scheme including algorithms for each module such as handling of a green plane & non green plane are proposed in this paper. Also coding of two residue sub planes (green and non green) by using adaptive Rice coding technique is used.

III. COMPARISON OF LOSSLESS COMPRESSION SCHEMES

Lossless compression schemes like JPEG2000, JPEG-LS and LCMI are explained and the performance of the each technique is compared with others.

A. JPEG 2000

JPEG2000 is the latest algorithm from the JPEG normalization group for still picture compression. JPEG (Joint Photographic Experts Group) is a compression algorithm suitable for grayscale or color images, such as continuous-tone photographs that contain more detail than can be reproduced on-screen or in print. JPEG is lossy, which means that it removes image data and may reduce image quality, but it attempts to reduce file size with the minimum loss of information. It can achieve much smaller file sizes than ZIP compression.

JPEG2000 [7, 8] is the new series of standards from the JPEG committee. The original standard for digital images (IS 10918-1, popularly referred to as JPEG) was developed with the major increase in computer technology since then, and lots of research, a new standard has been proposed capable of handling many more aspects than simply making the digital image files as small as possible. JPEG2000 has the following features:

- JPEG2000 uses wavelet analysis.
- JPEG2000 compression give better results on images (up to 20 per cent plus) like photographs with gradual transitions from color to color.
- It can allow an image to be retained without any distortion or loss. Simply sending the first part of such a lossless file to a receiver can result in a lossy version appearing (like present JPEG) - but continuing to transmit the file results in the fidelity getting better and better until the original image is restored.
- JPEG2000 compression method is typically lossy, a process that permanently removes some pixel data. Lossy JPEG or JPEG2000 compression can be applied to color images at various levels (minimum, low, medium, high, maximum).
- Lossless JPEG2000 compression scheme can also specified, so that no pixel data is removed. Compression for monochrome images is lossless.

Core coding system JPEG2000 is a wavelet based compression standard for still images with the same core system describing both lossless and lossy coding. For wavelet coefficient coding, the EBCOT algorithm (Embedded Block Coding with an Optimized Truncation) provides a rich scalable image stream which allows several progressive modes in transmission and visualization with multiple decompression possibilities.

The fundamental building blocks of a typical JPEG2000 encoder are shown in below figure 2.1.

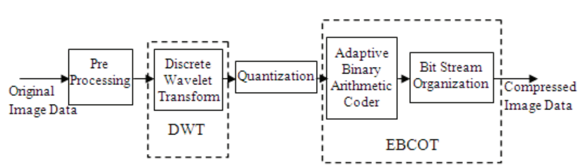


Figure 2.1: JPEG fundamental building blocks

The components present in the JPEG fundamental building block diagram include pre-processing, Discrete Wavelet Transform (DWT), quantization, and Embedded Block Coding with Optimized Truncation (EBCOT).

In JPEG2000 coding scheme, first a target image is divided into square regions, called tiles. The concept of tile in JPEG2000 reduces computational complexity of image coding, since each tile can be handled independently with each other. Then 2-D discrete wavelet transformation decomposes a tile into LL, LH, HL, HH subbands. LL subband is a low resolution version of the original tile and again is to be decomposed into four subbands recursively. This decomposition is called Mallat decomposition.

Wavelet coefficients in a code-block are quantized, then quantized coefficients are separated to sign bits and absolute values, and so-called bit-planes are generated from the bits of absolute values such that each bit-plane refers to all the bits of the same magnitude in all coefficients of the subband. Then bit-planes are coded one after another from the most significant one to the least significant one.

Coefficient bit modeling is a process to label bits of a bit-plane based on the statistical information through three different coding passes, which allows efficient compression by succeeding MQ-coder, an arithmetic coder. MQ-coder generates a set of packets, each of which is a part of the codestream constructed by a header information and the compressed image data originated from a specific layer, resolution level, and tile. Each coefficient bit of a bit-plane is encoded by one of the three passes according to significance state of eight nearest-neighbor coefficients. Each bit-plane is scanned by a series of significance propagation pass, magnitude refinement pass, and cleanup pass, and in one of these passes each coefficients is labeled by one of nineteen contexts. Then this context and a binary symbol are passed to successive MQ-coder. Binary symbols obtained by the coefficient bit modeling process are compressed by MQ-coder, which is a kind of binary arithmetic coder. MQ-coder compresses binary sequences by updating MPS (More Probable Symbol) and probability of LPS(Less Probable Symbol) of that context and returns an array of bytes.

B. JPEG-LS

JPEG-LS [9] was developed with the aim of providing a low complexity lossless image compression standard that could be able to offer better compression efficiency than lossless JPEG.

JPEG-LS (Joint Photographic Experts Group - Lossless) is an ISO/ITU standard [International Standards Organization / International Telecommunications Union] for low complexity lossless and near lossless encoding for continuous tone images. It is based on a fixed prediction encoding approach based on a neighborhood gradients followed by a Golomb type encoding, which is optimal for typical prediction error statistic distributions. JPEG-LS standard offers a lossless mode operation and a near-lossless one, in which every sample in the reconstructed image is guaranteed to differ from the corresponding value on the original image by up to a preset value, δ.

JPEG-LS is the first international compression standard that uses an adaptive entropy coding technique that requires only a single pass through the data and requires computational resources that are comparable to static Huffman coding.

The prediction and modeling units in JPEG-LS are based on the causal template depicted in figure 2.2, where x denotes the current sample, and a, b, c, and d, are neighboring samples in the relative positions. The dependence of a, b, c, d, and x, on the time index t has been deleted from the notation for simplicity. a, b, c, d, and x can be used to denote both the values of the samples and their locations. JPEG-LS limits image buffering requirement to one scan line.

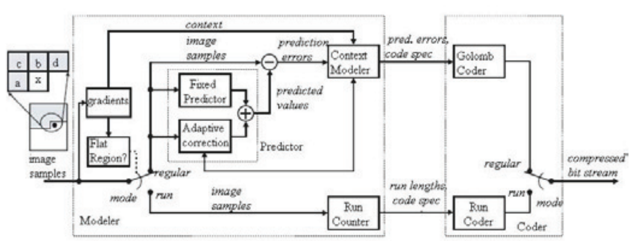


Figure 2.2: JPEG-LS Compression Scheme

C. Lossless Compression of Color Mosaic Images (LCMI)

Lossless compression of color mosaic images [10] poses a unique and interesting problem of spectral decorrelation of spatially interleaved R, G, and B samples. In this method reversible lossless spectral-spatial transforms are investigated, that can remove statistical redundancies in both spectral and spatial domains and discover that a particular wavelet decomposition scheme, called Mallat wavelet packet transform, is ideally suited to the task of decorrelating color mosaic data. Also a low-complexity adaptive context based Golomb-Rice coding technique is proposed to compress the coefficients of Mallat wavelet packet transform.

In this Compression scheme, an alternative approach of compressing color mosaic images directly without de-interleaving the color bands is considered. The strength and weakness of both DPCM (Differential Pulse Code Modulation) and wavelet based lossless coding methods in the above two different approaches are studied. The analysis leads to a new wavelet decomposition scheme that is well suited for lossless coding of Bayer pattern mosaic data directly without de-interleaving. This new wavelet decomposition has the nice property of decorrelating color samples both spatially and spectrally.

D. Comparison of JPEG2000, LPEG-LS & LCMI

The JPEG2000 standard provides a set of features that are of importance to many high-end and emerging applications by taking advantage of new technologies. The markets and applications better served by the JPEG2000 standard are internet, color facsimile, printing, scanning, digital photography, remote sensing, mobile, and medical image.

JPEG-LS was developed with the aim of providing a low complexity lossless image compression standard that could be able to offer better compression efficiency than lossless JPEG. At similar bitrates JPEG-LS generally offers better performance than JPEG algorithm. Moreover for JPEG-LS encoding, higher variance on compression ratios at different error levels, depending on the image characteristics can be observed. In JPEG-LS, complexity decreases for low entropy regions/images and for higher error level preset, due to the fact that in these conditions the encoder, which adopts a dual encoding mode (predictive/run-length), switches more frequently to the less expensive run-length mode.

The residuals of JPEG-LS for mosaic images deviate drastically from a Laplacian distribution, and they cannot even be modeled by a generalized Gaussian distribution. Unfortunately, the entropy code (Golomb–Rice code) of JPEG-LS assumes a Laplacian distribution of the prediction residuals. This severe mismatch between the model and the source explains the poor performance of JPEG-LS on mosaic images. Also it does not provide support for scalability, error resilience or any such functionality.

Various techniques for lossless coding of raw color mosaic images generated by CCD (Charge Coupled device) cameras of Bayer pattern were investigated. It turned out that the integer wavelet transform is ideally suited to the task, by offering efficient energy packing in both image and color spaces. Lossless Compression of Color Mosaic Images (LCMI) technique is a fast and practical codec for lossless compression of mosaic images. It is a simpler and faster lossless mosaic image codec based on integer Mallat packet transform and Rice code. This codec outperforms JPEG 2000 and JPEG-LS in both bit rate and speed.

IV. PREDICTION BASED LOSSLESS COMPRESSION SCHEME

Structure of proposed compression scheme(prediction based lossless CFA compression scheme) is shown in the figures 4.1(Encoder) and 4.2(Decoder).

First the CFA image is divided into two sub-images: a green sub-image which contains all green samples of the CFA image and a non-green sub-image which holds the red and the blue samples. The green sub-image is coded first and the non-green sub-image follows based on the green sub-image as reference. To reduce the spectral redundancy, the non-green sub-image is processed in color difference domain whereas the green sub-image is processed in the intensity domain as a reference for color difference content of the non-green sub-image.

Both sub-images are processed in raster scan sequence with the proposed context matching based prediction technique to remove the spatial dependency. The prediction residue planes of the two sub images are then entropy encoded sequentially with the proposed realization scheme of adaptive Rice coding.

The proposed prediction technique handles the green plane and the non green plane separately in a raster scan manner. It weights the neighboring samples such that the one has higher context similarity to that of the current sample contributes more to the current prediction. Accordingly, this prediction technique is referred to as a Context Matching Based Prediction (CMBP).

The green plane(green sub image) is handled first as a CFA image contains double number of green samples to that of red/blue samples and the correlation among green samples can be exploited easily as compared with that among red or blue samples. Accordingly, the green plane can be used as a good reference to estimate the color difference of a red or blue sample when handling the non green plane.

A. Prediction on the green plane

The green plane is raster scanned for the prediction process. During this process, all the prediction errors are recorded. Processed green samples are used in the prediction of pixels which have not yet been processed.

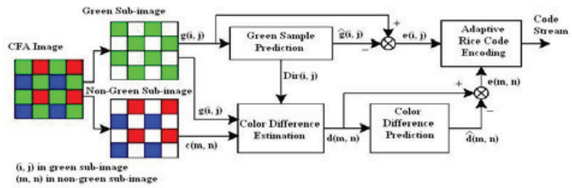


Figure 4.1: Structure of proposed compression scheme

Assume that, a particular green sample g(i, j) as shown in figure 4.2 is processed first. The four nearest processed neighboring green samples of g(i, j) form a candidate set.

$\phi_{g(i,j)}$ = {g(i, j-2), g(i-1, j-1), g(i-2, j), g(i-1. j+1)}

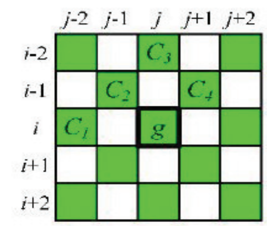


Figure 4.2 : Position of pixel included in the candidate set of a green sample

The candidates are ranked by comparing their support regions (i.e., context) with that of g(i, j). Support region of a green sample at a position (i, j) is defined as

Sg(i,j)= {(i, j-2), (i-1, j-1), (i-2, j), (i-1, j+1)}

The support region of a green sample at position (i, j) is shown in figure 4.3

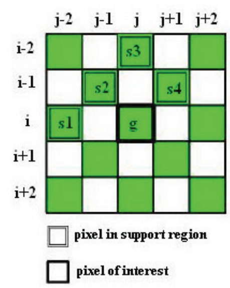


Figure 4.3 : The support region of a green sample

The matching extent of the support region g(i, j) and the support region of g(a, b) for g(a, b)

d(i,j)=|g(i, j-2) - g(a, b-2)| +| g(i-1, j-1) – g(a-1, b-1) | +| g(i-2, j) – g(a-2, b) | +| g(i-1, j+1) – g(a-1,b+1)|

Though a higher order distance, such as Euclidian distance, can be used instead of above equation to achieve a better matching performance. Euclidian distance or Euclidian metric is the ordinary distance between two points that one would measure with a ruler, and is given by Pythagorean formula.

But, however in the simulations it is found that the improvement was not significant enough to compensate for its high realization complexity. So this higher order distance, Euclidian distance in not used in the calculations.

Then the value of g(i, j) can then be predicted with a prediction filter as

$$\hat{g}(i, j) = \text{round}\left(\sum_{k=1}^{4} w_k g(m_k, n_k)\right)$$

where w_k for k=1, 2, 3, 4 are normalized weighting coefficients such that

$$\sum_{k=1}^{4} w_k = 1$$

Let Dir(i, j) = { W, NW, N, NE} be a direction vector associated with the sample g(i, j). It is defined as the direction pointed from the sample g(i, j) to g(i, j)'s first ranked candidate g(m1, n1). Four possible directions associated with a green sample is shown in figure 4.4.

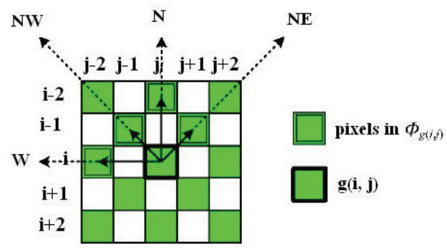


Figure 4.4 : Four possible directions associated with a green pixel

This definition applies to all green samples in the green sub-image. If the direction of g(i, j) is identical to the directions of all green samples in $S_{g(i,j)}$, pixel (i, j) will be considered in a homogenous region and $\hat{g}$ (i, j) will then be estimated to be g(m1, n1) directly.

In formulation

$\hat{g}$ (i, j) = g(m1, n1) if Dir(i, j) = Dir(a, b) $\forall$ (a, b) $\in$ $S_{g(i,j)}$

which implies that {w1, w2, w3, w4} = {1, 0, 0, 0}. Otherwise, g(i, j) is considered to be in a heterogeneous region and a predefined filter is used to estimate g(i, j) with above equation instead.

w_k (for k = 1, 2, 3, and 4) are obtained by quantizing the training result derived by the linear regression with the set of training images covering half of the test images. They are quantized to reduce the realization effort. After all, when g(i, j) is not in homogenous region, the coefficients of the prediction filter used to obtain the result presented are by {w1, w2, w3, w4} = {5/8, 2/8, 1/8, 0}, which allows the realization of to be achieved with only shift and addition operations.

Therefore, the predicted value of a green sample in heterogeneous region is given by

$\hat{g}$ (i, j) = round((5g(m_1 , n_1) + 2g(m_2 , n_2) + g(m_3 , n_3)) /8)

The prediction error is determined by taking the difference between original green sample and predicted green sample values.

$$e(i, j) = g(i, j) - \hat{g}(i, j)$$

Algorithm for handling of a green plane in CMBP is:

1. Raster scan the image and do the following steps [2]-[7] for each green sample g(i, j).
2. Determine the context difference

   D($S_{g(i,j)}$, $S_{g(m_\cdot,n_\cdot)}$) $\forall$ g(m, n) $\in$ $\phi_{g(i,j)}$

   and sort all candidates in the candidate set of g(i, j).
3. Determine direction of (i, j) i.e., Dir(i, j) and check for whether (i, j) is in homogenous region or heterogeneous region.
4. If (i, j) is in a homogeneous region, then {w1, w2, w3, w4}={1, 0, 0, 0}
5. Else if (i, j) is in a heterogenous region, then {w1, w2, w3, w4}={5/8, 2/8, 1/8, 0}
6. Calculate Predicted value of g(i, j).
7. Calculate Error between original and predicted value of a green sample

B. Prediction on the non-green plane

When a sample being processed is a red or blue sample i.e., a non-green sample in non-green plane, the prediction is carried out in the color difference domain instead of intensity domain as in green plane. This is done to remove inter channel redundancy.

Since the non-green plane is processed after the green plane, all green samples in a CFA image are known and can be exploited when processing the non-green plane. Besides, as the non-green plane is raster scanned in the prediction, the color difference values of all processed non-green samples in the CFA image should be determined first. And these color difference values can be exploited when predicting the color difference of a particular non-green sample.

Let d(p, q) be the green - red (or green - blue) color difference value of a non green sample c(p. q).

For any non-green sample c(i, j), its candidate set is

$\phi_{c(i,j)}$ = {d(i, j-2), d(i-2, j-2), d(i-2, j) , d(i-2, j+2)}

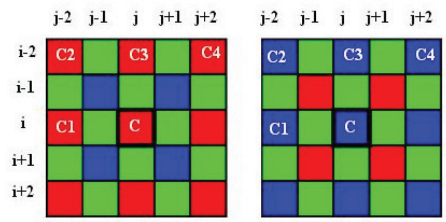


Figure 4.5 : Positions of pixels included in the candidate set of red and blue sample

and support region(context) of non-green sample c(i, j) is

$S_{c(i,j)}$ = {(i, j-1), (i-1, j), (i, j+1), (i+1, j)}

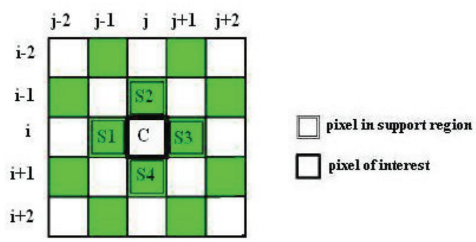


Figure 4.6 : Support region of a red/blue sample

figure 4.6 and figure 4.7 show respectively the positions of the pixels involved in the definition of $\phi_{c(i,j)}$ and $S_{c(i,j)}$.

The prediction for a non-green is carried out in the color difference domain. Specifically, the predicted color difference value of sample c(i, j) is given by

$$\hat{d}(i, j) = \text{round}\left(\sum_{k=1}^{4} w_k d(m_k, n_k)\right)$$

where w_k are the k^{th} predictor coefficient and d(m_k, n_k) are the k^{th} ranked candidate in $\phi_{c(i,j)}$ $\forall$ k = 1, 2, 3 and 4 such that

D($S_{c(i,j)}$, $S_{c(m_u,n_u)}$) $\leq$ D($S_{c(i,j)}$, $S_{c(m_v,n_v)}$) for 1 $\leq$ u $\leq$ v $\leq$ 4, where

D($S_{c(i,j)}$, $S_{c(m,n)}$)=| g(i, j-1) – g(m,n-1) |+ | g(i, j+1) – g(m,n+1) |+ | g(i-1, j) – g(m-1,n) |+| g(i+1, j) – g(m+1,n) |

In the prediction carried out in the green plane, region homogeneity is exploited to simplify the prediction filter and improve the prediction result. Theoretically, similar idea can be adopted in handling a non-green sample by considering the direction information of its neighboring samples. For any non-green sample c(i, j), if the directions of all green samples in $S_{c(i,j)}$ identical, pixel (i, j) can also be considered as in homogenous region.

Algorithm for handling of a non-green plane in CMBP

1. Raster scan the image and do the following steps [2]-[5] for each non green sample g(i, j).
2. Estimate color difference d(i, j) for a non green sample.
3. Determine the context differences

   D($S_{c(i,j)}$, $S_{c(m_u,n_u)}$) $\forall$ (m,n) $\in$ $\phi_{c(i,j)}$

   and sort all candidates in the candidate set of a non green sample.
4. Calculate predicted value of d(i, j), i.e., $\hat{d}(i,j)$.

5. Calculate error between original and predicted value of a color difference value.

In CMBP, all real green, red, and blue samples are encoded in a raster scan manner. The four samples used for predicting sample g(i, j) in figure 4.2 are g(i, j)'s closest processed neighboring samples of the same color. They have the highest correlation to g(i, j) in different directions and, hence can provide a good prediction result even in an edge region. A similar argument applies to explain why $\phi_{c(i,j)}$ is used when handling a non green sample c(i, j).

As for support region, no matter the concerned sample is green or not, its support is defined based on its four closest known green samples. This is because the green channel has a double sampling rate as compared with the other channels in a CFA image and, hence, provides a more reliable context for matching.

In the proposed compressed scheme, as green samples are encoded first in raster sequence, all green samples are known in the decoder, and hence, the support of a non green sample can be noncausal while the support of a green sample has to be causal. This noncausal support tightly and completely encloses the sample of interest. It models image features such as intensity gradient, edge orientation, and textures better such that more accurate support matching can be achieved.

When compressing the non green color plane, color difference information is exploited to remove the color spectral dependency. This section describes the proposed method for estimating the color difference value of a pixel without having a known green sample of the pixel.

In encoding phase, a CFA image is first divided into a green sub-image and a non-green sub image. The green sub image is coded first and the non green sub image follows based on the green sub image as reference.

To code a sub image, the sub image is raster scanned and each pixel is predicted with its four neighboring pixels by using the prediction scheme proposed.

The prediction error of pixel (i, j) in the CFA image, say e(i, j), is given by

$$e(i,j) = \begin{cases} g(i,j) - \hat{g}(i,j), & \text{if the pixel is in green sub image} \\ & \text{or} \\ d(i,j) - \hat{d}(i,j), & \text{if the pixel is non-green sub image} \end{cases}$$

where g(i, j) and d(i, j) are respectively, the real green sample value and the color difference value of the pixel (i, j). d(i, j) is estimated by the method described in section 4.3. $\hat{g}$ (i, j) and $\hat{d}$ (i, j), respectively, represent the predicted green intensity value and the predicted color difference value of pixel (i, j). E(i, j)'s from green sub-image is raster scanned and coded with Rice code first and then E(i, j)'s from non green sub image is coded with Rice code.

Rice code is employed to code E(i, j) because of its simplicity and high efficiency in handling exponentially distributed sources. When Rice code is used, each mapped residue E(i, j) is split into a Quotient Q and a Remainder R.

The Decoding process is just the reverse process of encoding. The green sub image is decoded first and then the non green sub image is decoded with the decoded green sub image as a reference. The original CFA image is reconstructed by combining the two sub images.

V. EXPERIMENTAL RESULTS

The algorithms have been evaluated with seven images from the JPEG 2000 test set, covering various types of imagery. The images "bike" (2048x2560) and "cafe" (2048x2560) are natural, "cmpnd1" (512x768) and "chart" (1688x2347) are compound documents consisting of text, photographs and computer graphics, "aerial2" (2048x2048) is an aerial photography, "target" (512x512) is a computer generated image and "us" (512x448) an ultra scan. All these images have a depth of 8 bits per pixel. Table 1 summarizes the lossless compression efficiency for all the test image

Reduced size in MB	JPEG200	LPEG-LS	LCMI	PCFA
bike	1.77	1.84	1.61	1.66
cafe	1.49	1.57	1.36	1.44
cmpnd1	3.77	6.44	3.23	6.02
chart	2.60	2.82	2.00	2.41
aerial2	1.47	1.51	1.43	1.48
target	3.76	3.66	2.59	8.70
us	2.63	3.04	2.41	2.94
average	**2.50**	**2.98**	**2.09**	**3.52**

Table 1: Reduced size of images after compression

Table 2 shows the execution times, for decompression

Execution times for decompression	JPEG200	LPEG-LS	LCMI	PCFA
bike	3.7	1.0	0.7	0.9
cafe	4.0	1.0	0.7	1.0
cmpnd1	6.7	1.0	1.6	2.2
chart	4.0	1.0	0.9	1.2
aerial2	4.1	1.0	0.7	0.8
target	3.9	1.0	0.9	1.3
us	3.9	1.0	0.7	1.1
average	**4.3**	**1.0**	**0.9**	**1.2**

Table 2: Execution times of decompression

VI. CONCLUSION

A lossless compression scheme for bayer CFA images is proposed. This scheme separates a CFA image into a green sub-image and a non-green sub-image and then encodes them separately with predictive coding. The prediction is carried out in the intensity domain for the green sub-image while it is carried out in the color difference domain for the non-green sub-image. In both cases, a context matching technique is used to rank the neighboring pixels of a pixel for predicting the existing sample value of the pixel. The prediction residues originated from the red, the green, and the blue samples of the CFA images are then separately encoded by using adaptive rice coding technique.

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