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Prediction based Lossless compression scheme for Bayer color filter array image

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***Abstract*— In most digital cameras Bayer color filter array images captured and demosaicing is generally carried out before compression. Recently it was compression first scheme out perform the conventional demosaicing first schemes in terms of output image quality. An efficient prediction based lossless compression scheme for Bayer filter color images proposed**

***Index Terms*—Bayer Color filter array, Lossless compression, Green prediction, Non-green prediction, Adaptive color difference.**

I.Introduction

BAYER COLOR FILTER ARRAY

A Bayer Filter color array usually coated over the sensors in these cameras to record only one of the three colors components at each pixel location. The resultant image is referred to as a CFA image.

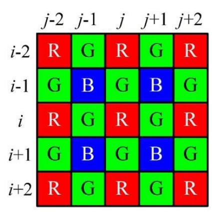


Fig:(1) Bayer Patter has Red sample in center

Fig shows the Bayer Patter has Red sample in center, compressed for storage. Then it was inefficient in a way the demosaicing process always introduce some redundancy which should eventually be removed in the following compression step. We do the compression before demosaicing digital cameras can have a simpler design and low power consumption as computationally heavy process like demosaicing can be carried in an offline powerful personal computer. This motivates the demand of CFA image compression schemes.

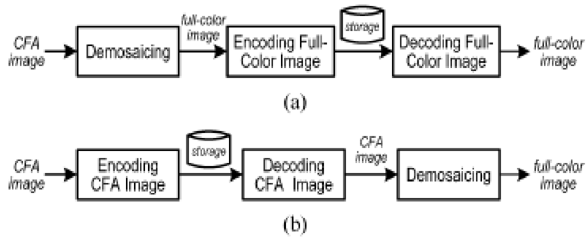


Fig 2: single sensor camera imaging chain (a) demosaicing and (b) Compression

II.PRESENT SCHEMES USED

There are different schemes present in the market such as

- Lossy compression scheme
- JPEG2000

So now we have to look the drawbacks of present methods.

- Lossy schemes compress a CFA Image by discarding its visually redundant information.
- This scheme visually yields a higher compression ratio as compared with the lossless schemes.
- JPEG-2000 is used to encode a CFA image but only a fair performance can be attained.
- JPEG-2000 is very expensive method to compress the images.

III. PROPOSED SCHEME

A Prediction based lossless CFA compression scheme is proposed. It divides a CFA images into two sub-images:
(a) A green sub-image which contains all green samples of the CFA image
(b) Non-green sub image which contains the red and blue samples in the CFA image.
This system is mainly consists of two parts

- Encoder
- Decoder

Encoder:

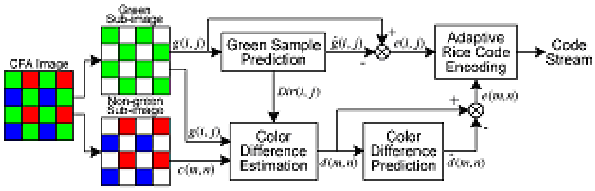


Fig 3: Structure of proposed scheme

Green Subimage is coded first and the Non green Subimage follows based on green subimage as reference and To reduce the spectral redundancy, the nongreen subimage is processed in the color difference domain whereas the green subimage is processed in the intensity domain as a reference for the color difference content of the nongreen subimage. Both subimages are processed in raster scan sequence with context matching based prediction technique to remove the spatial dependency. The prediction residue planes of the two subimages are then entropy encoded sequentially with our proposed realization scheme of adaptive Rice code.

IV. WORKING OF THE SCHEME

This proposed scheme is mainly working on Prediction on the green plane and Prediction on the Non-green plane.

Prediction on the green plane

As the green plane is raster scanned during the prediction and all prediction errors are recorded. Now processing a particular green plane the four nearest processed neighboring samples of g (i,j) form a candidate set

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

We can find the directions associated with the green pixels it need some process.

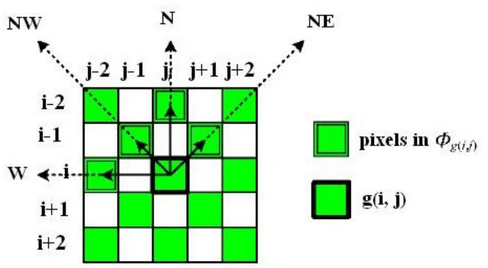


Fig 4: Four possible directions associated with green pixel

Let g(mk,nk)Є Φg(i,j) for k=1,2,3,4 be the four ranked candidates of sample g(i,j) Э(Sg(i,j), Sg(mu,nu)) <= D(Sg(i,j), Sg(mv,nv)) for 1<=u<=v<=4

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

If the directions of g(i,j) is identical to the directions of all green samples in Sg(i,j), pixel (i,j) will be considered in a homogenous region and prediction of g(i,j) is

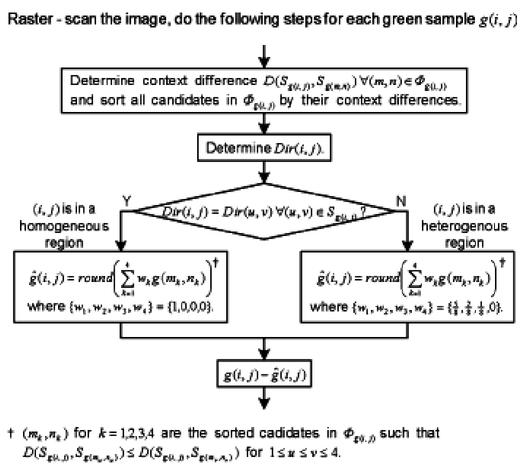
$$\left.\begin{array}{l} \hat{g}(i, j) = g(m1, n1) \\ If\ Dir(i, j) = Dir(a, b) \ \forall\ (a, b) \in S_{g(i,j)} \text{ ---(2)} \\ \text{i.e. } \{w1,w2,w3,w4\}=\{1,0,0,0\} \end{array}\right\}$$

Else the g(i,j) is in heterogenous region and predicted value of g(i,j) is

$$\hat{g}(i, j) = round\left(\sum_{k=1}^{4} w_k g(m_k, n_k) \right) \text{-----(3)}$$

i.e. {w1,w2,w3,w4}={5/8,2/8,1/8,0}

FLOW CHART FOR PREDICTION ON THE GREEN PLANE



Adaptive color difference estimation for non green plane

When compressing the nongreen color plane, color difference information is exploited to remove the color spectral dependency.

Let c(m,n) be the intensity value at a non green sampling position(m,n). Green-Red(Green-Blue) color difference of pixel (m,n) is

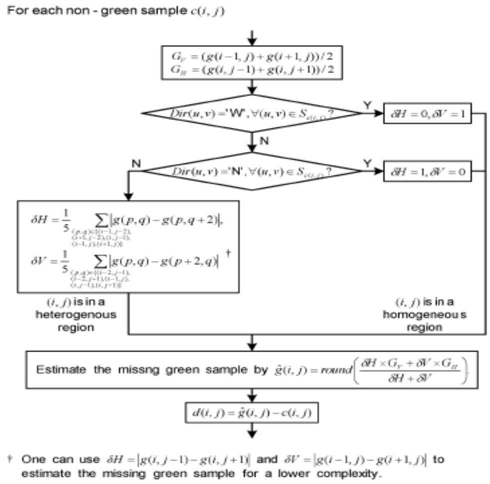
d(m,n)=g'(m,n)-c(m,n)

g'(m,n) à estimated green component intensity value

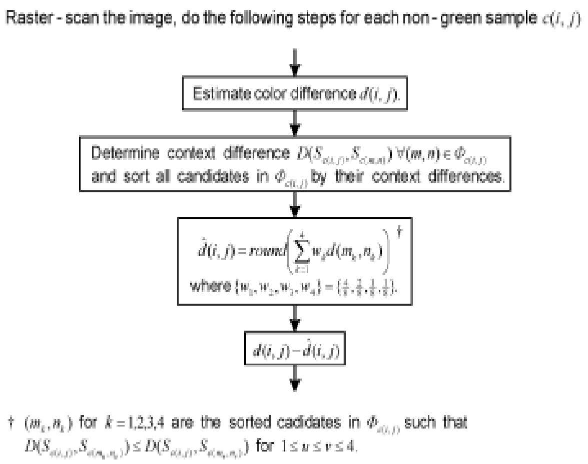
g'(m,n)=round((δ H*Gv+δV*GH)/(δH+ δV))

GH=(g(m,n-1)+g(m,n+1))/2 and

Gv=(g(m+1,n)+g(m+1,n))/2



Prediction on the non green plane



Color difference prediction of a non green sample c(i,j) with color difference value d(i,j) is

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

Where {w1, w2, w3, w4}={4/8, 2/8, 1/8, 1/8}

Where k is predictor coefficient
d(mk,nk) is kth ranked candidate in Φc(i,j)

Compression scheme

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

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

where *g(i, j), d(i, j)* are respectively, the real green sample value and the color difference value of pixel *(i, j)*

The error residue *e(i, j)* is then mapped to a nonnegative integer as follows to reshape its value distribution to an exponential one from a Laplacian one.

$$E(i, j) = \begin{cases} -2 * e(i,\ j), & \text{if } e(i,\ j) \le 0 \\ 2 * e(i,\ j), & \text{Otherwise.} \end{cases} \quad \text{---(5)}$$

The *E(i, j)* 's from the green sub-image are raster scanned and coded with Rice code first. 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

$$Q = floor\ (\ E(i, j)\ /\ 2^k\ )$$

$$R = E(i, j) \bmod (\ 2^k\ )$$

Where parameter k is a non negative integer
Quotient and Remainder are then saved for storage and transmission.

The Length of code word used for representing *E(i, j)* is *k* dependent and is given by

$$L(E(i, j)\ |\ k) = floor\ (E(i, j)/2) + 1 + k \quad \text{---(6)}$$

Parameter k is critical to the compression performance as it determines the code length of *E(i, j)*

Optimal parameter K is given by

$$K = max\{0, ceil(\ \log_2 (log\Phi\ /\ log\ \rho^{-1}\ )\ )\} \text{-----(7)}$$

Where Φ = ($\sqrt{5}$ +1) / 2 is the golden ratio.

For a geometric source with distribution parameter color spaces I As long as is **μ** known, parameter **ρ**, and, hence, the optimal coding parameter ***k*** for the whole source can be determined easily.

M is estimated adaptively in course of Encoding

$$\tilde{\mu} = round\left(\frac{\alpha\tilde{\mu}_p + M_{i,j}}{1+\alpha}\right) \quad \text{and-(8)}$$

$$M_{i,j} = \left(\frac{1}{4} \sum_{(a,b)\in\varsigma_{i,j}} E(a,b)\right) \text{--(9)}$$

When coding E(i, j) of green plane is defined to be

$$\varsigma_{i,j} = \{\ (i, j\text{-}2),\ (\ i\text{-}1, j\text{-}1),\ (\ i\text{-}2, j),\ (\ i\text{-}1, j\text{+}1)\ \}$$

When coding E(i, j) of non green plane is defined to be

$\varsigma_{i,j}$ = { (i, j-2), (i-2, j-2), (i-2, j), (i-2, j+2) }

Decoding Process:

Decoding Process is just reverse process of Encoding. Green Sub-image is decoded first and then the non-green sub-image is decoded with the decoded green sub-image as a reference. Original CFA Image is then reconstructed by combining the two sub images.

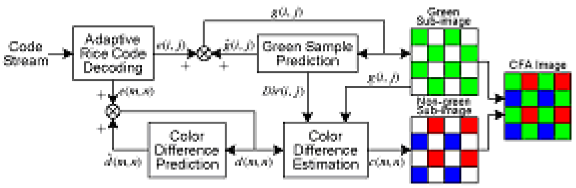
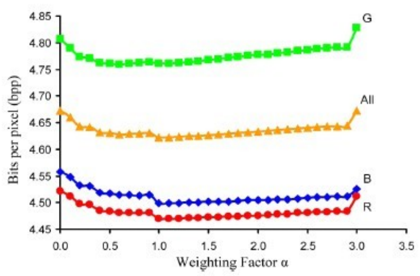


Fig 5: Structure of Decoder

BITRATE ANALYSIS



Average output bit rates of the proposed compression scheme achieved with different α values.

From the above fig, it shows that α = 1 can provide a good compression performance. We assume the prediction residue is a local variable and estimate the mean of its value distribution adaptively. The divisor used to generate the Rice code is then adjusted accordingly so as to improve the efficiency of Rice code.

V. COMPRESSION PERFORMANCE

Simulations were carried out to evaluate the performance of proposed compression scheme. 24-bit color images of size 512*768 were sub- sampled according to the Bayer pattern to form 8 bit testing CFA images. These Images are directly coded by the proposed compression scheme for evaluation.

Some representative Lossless compression schemes such as JPEG-LS, JPEG 2000(lossless mode) and LCMI were used for comparison of Results.

Table – I

Sno	JPEG LS	JPEG 2000	Proposed
Image 1	5.467	5.039	4.803
Image 2	6.188	5.218	4.847
Image 3	6.828	4.525	3.847

If we alter the values of weighting factor then we get improved results in terms of compression ratio and also reduce the bit rates of CFA.

Table-II

	Overall CFA Bit Rate (in bpp)	Compression Ratio
α =0	4.9496	1.6163
α =0.6	4.8496	1.6496
α =0.8	4.8437	1.6516
α =1	4.8366	1.6537

ADVANTAGES OF PROPOSED METHOD

We can reduce the spectral redundancy mean time and also can get high quality image. Reducing the sensors in digital cameras from 3 to 1. Low complexity to design. Compare with JPEG2000 it gives better performance.

VI. EXPERIMENTAL RESULTS

VII. CONCLUSION

CFA image encodes the sub-image separately with predictive coding Lossless prediction is carried out in the intensity domain for the green. While it is carried out in the color difference domain for the non green

VIII.ACKNOWLEDGMENT

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