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Designing of Color Filter Arrays in the Frequency Domain

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ABSTRACT: -- In digital color imaging, the raw image is typically obtained via a single sensor covered by a color filter array (CFA), which allows only one color component to be measured at each pixel. The procedure to reconstruct a full color image from the raw image is known as demosaicking. Since the CFA may cause irreversible visual artifacts, the CFA as well as the demosaicking algorithm is crucial to the quality of demosaicked images. Fortunately, the design of CFAs in the frequency domain provides a theoretical approach to handling this issue. However, almost all the existing design methods in the frequency domain involve considerable human effort. In this paper, we present a new method to automatically design CFAs in the frequency domain. Our method is based on the frequency structure representation of mosaicked images. We utilize a multi-objective optimization approach to propose frequency structure candidates, in which the overlap among the frequency components of images mosaicked with the CFA is minimized. Then we optimize parameters for each candidate, which is formulated as a constrained optimization problem. We use the alternating direction method (ADM) to solve it. Our parameter optimization method is applicable to arbitrary frequency structures, including those with conjugate replicas of chrominance components. Experiments on benchmark images confirm the advantage of the proposed method.

KEYWORDS: Color filter array (CFA), demosaicking, multi objective optimization, alternating direction method (ADM).

I.INTRODUCTION

Color images contain at least three color components at each pixel, such as red (R), green (G), and blue (B), or cyan (C), magenta (M), and yellow (Y). To produce a color image, a digital camera would need one sensor for each color component to record its values However; multiple sensors are expensive and have difficulty in precise registration. So most digital cameras use a single sensor covered by a color filter array (CFA). A CFA is a hardware which has the same size as the sensor and allows only one color Component to be sensed at each pixel. The process to recover a full color image from the image obtained from a single sensor with a CFA is called demosaicking. Both the CFA and the demosaicking algorithm affect the quality of the reconstructed full color image. The Bayer CFA [1] is the most popular CFA in the consumer market (Fig. 1(1a)) and hence the majority of demosaicking algorithms are proposed for it. The Bayer CFA was designed based on the human visual system's (HVS) greater sensitivity to green light. However, spectral characteristic analysis has shown that aliasing artifacts are inherent to the Bayer CFA. We can see from Fig. 1(2a) that there are chrominance components of the image mosaicked with Bayer CFA located on the horizontal and the vertical axes, where the luminance component has a high spectral density. To overcome the limitation of the Bayer CFA, many other CFAs have been proposed Since the seminal work by Alleysson et al, the frequency representation of mosaicked images has provided new insights into demosaicking algorithm, and CFA design. The CFA design in the frequency domain [3], [4], [5] provides a theoretical approach to producing full color images with fewer visual artifacts.

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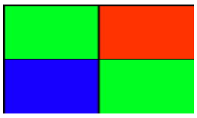
II.FREQUENCY REPRESENTATION OF A CFA

For converting the spatial domain Bayer CFA pattern into frequency representation we will perform the two dimensional discrete Fourier transform



$$\Rightarrow \text{DFT} \begin{pmatrix} G & R \\ B & G \end{pmatrix} \Rightarrow =1/4 \begin{pmatrix} R+2G+B & B-R \\ R-B & 2G-R-B \end{pmatrix} = \begin{pmatrix} \mathbf{F_L} & \mathbf{F_{C2}} \\ \mathbf{-F_{C2}} & \mathbf{F_{C1}} \end{pmatrix}$$

As luma is the sum of RGB L=R+G+B and the chroma is specify as any color differences among RGB C=(RorGorB)-(RorGorB)we will specify the frequency terms for one periodic array
As it is linear transform we can rewrite the above matrix as fallows

$$\begin{pmatrix} R+2G+B & B-R \\ R-B & 2G-R-B \end{pmatrix} \Rightarrow \begin{pmatrix} F_L \\ F_{C1} \\ F_{C2} \end{pmatrix} = 1/4 \begin{pmatrix} 1 & 2 & 1 \\ -1 & 2 & -1 \\ -1 & 0 & 1 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

The above matrix representation can be written as $\mathbf{F_S = T\,(R\ G\ B)^T} \Rightarrow \begin{pmatrix} \mathbf{R} \\ \mathbf{G} \\ \mathbf{B} \end{pmatrix} = \mathbf{T^{-1}.F_S}$

Where F_s= Frequency structure matrix for one periodic array
T = Multiplexing matrix

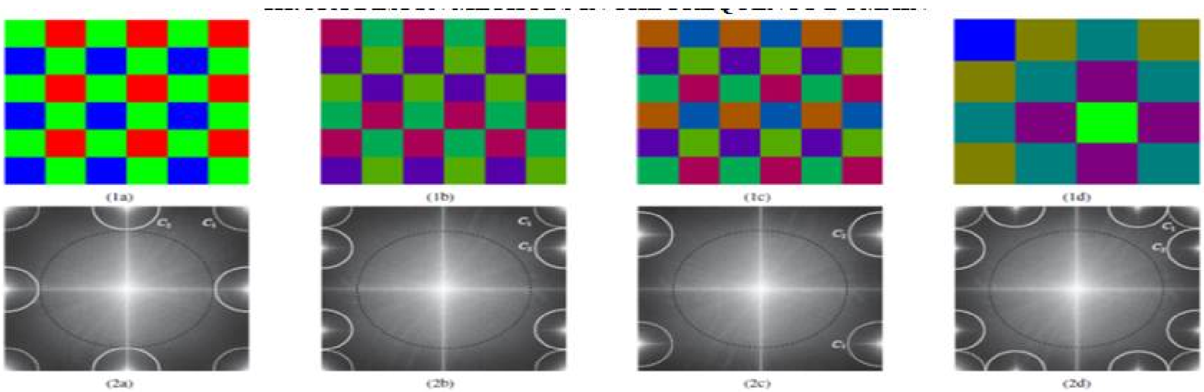
For getting the demosaicked image first we should find the luma and the chromas by filtering, second to find the RGB values by the inverse as follows from the above equation

$\mathbf{T^{-1}}$ Will be the demosaicking matrix through which we can reconstruct full color image with the recorded colors of RGB at the color filter array mask With this procedure we can generate frequency structure matrix, multiplexing matrix and demosaicking matrices for any size of CFA which is arbitrary rectangular and periodic with the colors of

R,G,B,C(G+B/2),M(R+B/2,Y(R+G/2),W(R+G+B/3)

R=Red C=Cyan G=Green M=Magenta W=White B=Blue Y=Yellow

III.CFA DESIGN METHODS IN THE FREQUENCY DOMAIN



a.Bayer

$$\begin{pmatrix} F_L & F_{C2} \\ -F_{C2} & F_{C1} \end{pmatrix}$$

(3a)

b.Hiraka

$$\begin{pmatrix} F_L & 0 \\ 0 & F^*_{C2} \\ 0 & F_{C1} \\ 0 & F_{C2} \end{pmatrix}$$

(3b)

c.Condat

$$\begin{pmatrix} F_L & 0 \\ 0 & F_{C1} \\ 0 & F_{C2} \end{pmatrix}$$

(3c)

d.Hao

$$\begin{pmatrix} F_L & 0 & 0 & 0 \\ 0 & 0 & F_{C2} & 0 \\ 0 & F_{C2} & F_{C1} & F_{C2} \\ 0 & 0 & F_{C2} & 0 \end{pmatrix}$$

(3d)

Fig1:- Four existing CFA patterns in frequency domain and their frequency spctra

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Second row are the average spectra of all 24 images of kodak dataset in mosaiced with the corresponding cfa in first row matrices are the corresponding frequency structures of the CFA 's in the first row

The frequency representation of mosaicked images also allows us to understand the visual artifacts in demosaicked images as the aliasing between luma and modulated chromas, namely, if luma and modulated chromas overlap in the frequency domain, some frequency components contain sum of luma and chromas instead of each of them separately. Then the demosaicking algorithm can produce visual artifacts when it recovers luma and chroma independently thus we consider that these artifacts are inherent to the CFAs instead this motivates the design of CFAs by reducing the spectra overlap between luma and modulated chromas. According to the motivation Hirakawa[3],Condat[4],Hwo[5] CFA design methods in the frequency domain have been presented Inspired by the spectral characteristic analysis of Bayer CFA [2], Hirakawa and Wolfe [3] proposed the first CFA design method in the frequency domain. Instead of directly using the RGB basis, they empirically chose G, R- G, and B- G as the basis to decorrelate the image channels. Let c(n) = $(c_R(n), c_G(n), c_B(n))^T$ be the color pixel of the CFA at n, where $n \epsilon Z^2$ and Z denotes the set of integers. So it is physically realizable, i.e., it is real, non-negative and lies in [0,1]. They further required that it satisfies $c_R(n) + c_G(n) + c_B(n) = \Upsilon$,Let $x(n) = (x_R(n),x_G(n),x_B(n))^T$ denote the color pixel of the full color image at n, $x_{C1} = x_R - x_G$,and $x_{C2} = x_B - x_G$. Then the noise-free mosaicked image y would be:

$$y(n) = c(n)^T x(n) = c(n)^T I x(n)$$

$$= C(n)^T \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 1 \end{pmatrix} X(n) = \begin{pmatrix} {}^{C}R(n) \\ \Upsilon \\ {}^{C}B(n) \end{pmatrix} \begin{pmatrix} \chi_{C1}(n) \\ \chi_{G}(n) \\ \chi_{C2}(n) \end{pmatrix} \Rightarrow \begin{pmatrix} {}^{C}R(n) \\ \Upsilon \\ {}^{C}B(n) \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ \frac{-\mu 1}{\Upsilon} & 1 & \frac{-\mu 2}{\Upsilon} \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ \frac{\mu 1}{\Upsilon} & 1 & \frac{\mu 2}{\Upsilon} \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \chi_{C1}(n) \\ \chi_{G}(n) \\ \chi_{C2}(n) \end{pmatrix}$$

$$= ({}^{C}R(n)-\mu_1, \Upsilon, {}^{C}B(n)-\mu_2) \begin{pmatrix} \chi_{C1}(n) \\ \chi_{L}(n) \\ \chi_{C2}(n) \end{pmatrix}$$

Where $x_L(n) = x_G(n) + \left(\frac{\mu 1}{\Upsilon}\right) x_{C1}(n) + \left(\frac{\mu 2}{\Upsilon}\right) x_{C2}(n)$

Represent the luma,x_{C1} and x_{C2} represent the two chromas, and (.)T denotes matrix transpose. So all the parameters are $\boldsymbol{\Upsilon}, \boldsymbol{\mu_1}$ $\boldsymbol{\mu_2}$, and the Fourier coefficients of the Fourier transforms of c_R and c_B. They next conducted parameter search, so that the resultant CFA is physically realizable and the chromas are modulated far away from the luma. Minimizing the overlap between luma and chromas is achieved by enforcing a constraint during parameter search that chromas should be located at the spectrum border. They also empirically imposed that the red-green-blue ratio in luma should be 1 : 1 : 1 or 1 : 2 : 1. The spectrum of images mosaicked with their proposed CFA is shown in Fig. 1(2b). We can see that the modulated chromas are far away from the center and the horizontal and the vertical axes, where the luma has a high spectrum density. We can also see from Fig. 1(2a) that the modulated chromas of Bayer CFA overlap with the luma on the horizontal and the vertical axes.

Condat [4] followed the approach of Hirakawa and Wolfe [3]. However, he argued that for modern cameras the robustness of a CFA to noise is more important than to aliasing, especially in low-light conditions. So he proposed a new CFA that is robust to both aliasing and noise (Fig. 1(1c)). In comparison with the work of Hirakawa and Wolfe, he used an orthonormal basis: $L = (R + G + B)/\sqrt{3}$, $C_1 = (-R+2G-B)/\sqrt{6}$ $C2=(R-B)/\sqrt{2}$ which is claimed to maximally de correlate the image channels. So his model was simplified as:

$$Y(n) = C(n)^T \frac{1}{6} \begin{pmatrix} 2 & -1 & 3 \\ 2 & 2 & 0 \\ 2 & -1` & -3 \end{pmatrix} \mathrm{diag} \begin{pmatrix} \sqrt{3} \\ \sqrt{6} \\ \sqrt{2} \end{pmatrix} \mathrm{diag} \begin{pmatrix} \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 \\ -1 & 2 & -1 \\ 1 & 0 & -1 \end{pmatrix} X(n)$$

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$$= (\Upsilon/\sqrt{3}, C_1(n), C_2(n),)(\chi_L(n), \chi_{c1}(n), \chi_{C2}(n))^T$$

Where $C_1(n)=(-C_R(n)+2C_G(n)-C_B(n))/\sqrt{6}$, $C_2(n)=(C_R(n)-C_B(n))/\sqrt{2}$,

and dag(.) converts a vector to a diagonal matrix whose j-th diagonal element is the j-th element of the vector. Then he used a constructive approach to manually determine all the parameters step by step. Different from the other design methods, he selected parameters to simultaneously maximize the minimum distance between luma and chromas and the sensitivity of the CFA, which can reduce the noise level in demosaicked images. In order to maximally reduce the overlap between luma and chromas, he imposed that the two chromas are conjugate and each of them has only one replica. The designed 2×3 CFA is shown in Fig. 1(1c). It has six distinct color components. The spectrum of his CFA is shown in Fig. 1(2c).

Based on the frequency structure, Hao et al. [5] designed CFAs from a new perspective. The design of CFAs leaves many parameters to be chosen. Since the luma and the two chromas constitute a basis, there exists an invertible conversion between it and the RGB basis. Formally, we have the following relationships

$$(F_L, F_{C1}, F_{C2})^T = M\,(R,G,B)^T$$

Where F_L, F_{C1} , and F_{C2} denote the luma and the two chromas, respectively, R, G, and B refer to the red, green, and blue color components, respectively, $M \epsilon C^{3\times3}$ is invertible and is called the color transformation matrix, and C denotes the set of complex numbers. In frequency selection based demosaicking, the RGB full color image is recovered from the estimated F_L, F_{C1} , and F_{C2} via solving (5). However, the estimations of F_L, F_{C1} , and F_{C2} contain errors. Accordingly, one should control the error in demosaicked images that results from the estimation errors. Formally, we denote $y = (\Delta F_L, \Delta F_{C1}, \Delta F_{C2})^T$ as the estimation errors and $x = (\Delta R, \Delta G, \Delta B)^T$ as the error that results from y. Then according to (5), we have y = Mx. Consequently, the amplification factor of estimation errors is:

$$\frac{\|x\|_2}{\|y\|_2} = \frac{\|M^{-1}\|}{\|y\|_2} \leq \max_{y\neq0} \frac{\|M^{-1}y\|_2}{\|y\|_2} = \|M^{-1}\|_2$$

where M^{-1} is the inverse of M, $\|M^{-1}\|$ is the spectral norm of M^{-1} which is its largest singular value, and $\|x\|_2$ is the l_2 norm of vector x. This implies that decreasing $\|M\|_2$ can greatly enhance the numerical stability of color transformation. With the help of frequency structure, they formulated parameter optimization as a constrained optimization problem to maximize the numerical stability of the color transformation. Meanwhile, the problem of minimizing the aliasing between luma and chromas is converted into a frequency structure selection problem. For a selected frequency structure, Hao etal formulated the parameter optimization problem as follows:

$$\min_{M} \|M^{-1}\|_F \quad \text{s.t.} \quad C_j \in [0,1], \sum_j C_j = 1,\ j \in \{R,G,B\},$$

where 1 denotes the all-one matrix, c_R, c_G, and c_B denote the three channels of the CFA, and $\|M^{-1}\|_F$ is the Frobenius norm of M^{-1} to approximate $\|M^{-1}\|_F$They further imposed that M should be real, which implies that the frequency structures cannot contain conjugate replicas of the chromas. Then they proposed a geometric method to solve (5). Although they provided several guidelines for manual frequency structure choice, the computation for all the candidates still requires immense resources for a reasonably sized CFA pattern. More-over, the proposed geometric method needs the user to specify the optimal triangle, which contains the origin as its inner point and minimizes $\|M^{-1}\|_F$

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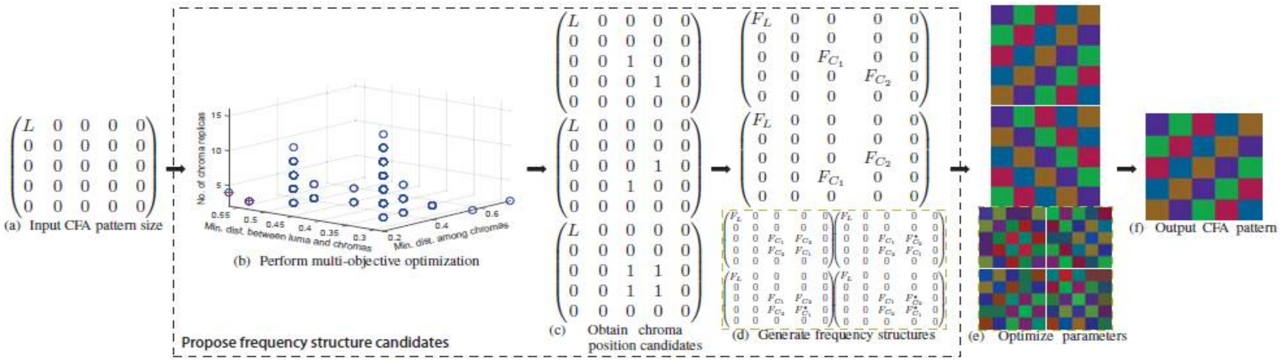
IV.PROPOSED CFA DESIGN METHOD



.

Fig:-2 process of proposed method n brief steps

A. Propose Frequency Structure Candidates:

For a given CFA pattern size, we argue that the minimum distance between luma and chromas as well as between chromas of the frequency structure should be as large as possible. They are our first two objectives. If the given size of a CFA pattern is larger than 2 × 2, all chromas should not locate on the horizontal and the vertical axes of luma. Moreover, with redundant chroma replicas, we can estimate each chroma more accurately by fusing all its estimations adaptively. So the number of chroma replicas should also be as large as possible , which is our third objective. The three objectives are in conflict and hence we cannot find a single solution that is optimal for all of them. We propose a multi-objective optimization approach to find an appropriately balanced solution.

1) Multi-objective Optimization:

Multi-objective optimization refers to the simultaneous minimization or maximization of more than one objective functions. More formally, it studies the problem as follows:

$$\max_{x}\{f_1(x), f_2(x), \ldots\ldots, f_m(x)\} \quad s.t\; x \in \Omega$$

Where we have m ≥ 2 objective functions fj and want to maximize all the functions simultaneously, x is the decision variable, and Ω is the feasible region which can be formed by various constraints. Note that we assume that all the objective functions are to be maximized for simplicity.

If an objective function fj is to be minimized, it is equivalent to maximizing the function −fj. The objective functions can be incommensurable, i.e., in different units. For example, in Fig. 3, f1 ∈ [0, 30] and f2 ∈ [0, 3] have different value ranges. Also, there is only partial ordering in the objective space, e.g., we cannot compare (f1(x1), f2(x1))T = (3, 2.5)T with (f1(x2), f2(x2))T = (2, 3)T. Furthermore, in general, there may be partial conflicts among the objective functions, i.e., maximizing one function can decrease the values of the others. Because of the possible incommensurability and conflict among the objective functions, it is not possible to composite a global objective function as a weighted sum of all the objective functions, or find a single solution that is optimal w.r.t. every objective function. The solutions of a multi-objective optimization problem are called Pareto optimal solutions. We state a more formal definition in the following:

Definition 1: A decision variable x1 is said to be dominated by x2 if fj(x1) ≤ fj(x2) for all j = 1, 2. . . m and fk(x1) < fk(x2) for at least one index k.

For example, in Fig. 3, p1 is dominated by p0, and q1 and q2 are both dominated by q0. Since f2 (p0) > f2(q0) and f1(p0) < f1(q0), p0 and q0 are not dominated by each other.

Definition 2: A decision variable x∗ ∈ Ω is Pareto optimal if x∗ cannot be dominated by any variable x ∈ Ω.

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In Fig. 3, p0 and q0 cannot be dominated by any other feasible points. So they are both Pareto optimal to the problem. All the Pareto optimal solutions constitute the Pareto optimal set of the problem, e.g., {p0, q0} is the Pareto optimal set to the multi-objective optimization problem illustrated in Fig. 3.

2) Obtain Chroma Position Candidates: Note that the only luma is fixed at the top-left of frequency (0,0) in the frequency structure (see Fig. 2(a)). So we only need to choose the replicas of the two chromas and their positions in the matrix to finally determine a frequency structure. As noted before, the rows and columns of frequency structure are indexed by (0, 1, · · · , $n_r - 1$) and (0, 1, …. , $n_c - 1$), which represent the frequency points of $2\pi\left(0,\frac{1}{n_r},\ldots,\frac{n_r-1}{n_r}\right)$ and, $2\pi\left(0,\frac{1}{n_c},\ldots,\frac{n_c-1}{n_c}\right)$ respectively, where $n_r \times n_c$ is the CFA pattern size. In the following discussion, we omit 2π from all frequency points for simplicity. Since the designed CFA is real, once the position of a chroma frequency point (n_x/n_c,n_y/n_r) in the frequency structure is chosen, the position ((1−n_x/n_c) mod 1, (1−n_y/n_r) mod 1) must also be chosen , where mod is the modulo operation, nx ∈ {0, 1, …. , $n_c - 1$}, and n y ∈ {0, 1, ·….., $n_r - 1$}. If the two positions are different, we call them a conjugate position pair, otherwise we say that the position is self-conjugate, e.g., (12, 12), or (12, 0). If the matrix has m p conjugate position pairs and ms self-conjugate positions, there are $2^{m_p+m_s} - m_s - 1$feasible chroma position allocations. Also, if the CFA pattern size is larger than 2× 2, we first discard those allocations that contain chroma positions on the horizontal and the vertical axes of luma. Then we perform multi-objective optimization on the rest of allocations.

$\max_x\{f_1(x), f_2(x), f_3(x)\}$ ($s.t\ x$the set of feasible chroma position allocations)

Where f1 denotes “the minimum distance between luma and chroma positions”, f2 denotes “the minimum distance between chroma positions”, and f3 denotes “the number of chroma replicas”. Since frequency structure is periodic in both horizontal and vertical directions (please read the caption of Fig. 1), we compute the distance between two positions in it as follows. Suppose the two positions are (x1, y1) and (x2, y2). Then the distances along the horizontal and the vertical directions are d x = min(|x1 − x2|, 1 −|x1 − x2|) and d y = min(|y1 − y2|, 1 −|y1 − y2|), respectively, where |x| is the absolute value of the scalar x. So the Euclidean distance between the two positions is $\sqrt{d_x^2 + d_y^2}$. We take the frequency structure F_H in (1) as an example. The distance between F_L and $F_{c_1}$is $\sqrt{min(1/2,1-1/2)^2 + min(2/4,1-2/4)^2} = \sqrt{2}/2$. The distance between F_L and $F_{c_2}^*$ is $\sqrt{min(1/2,1-1/2)^2 + min(1/4,1-1/4)^2} = \sqrt{5}/4$. The distance between FL and FC2 is $\sqrt{min(1/2,1-1/2)^2 + min(3/4,1-3/4)^2} = \sqrt{5}/4$. So f1 (FH) is min (√2/2, √5/4) = √5/4. Similarly, we can compute the $(f_{2,}F_H)$Thus solving problem is equivalent to finding the Pareto optimal set from a given point set (see Fig. 3). We use the non-dominated sorting scheme to solve it . The objective value of f1 for the Bayer CFA is 0.5. Since f1 is more important than f2 and f3, we reject the chroma position candidates whose objective values of f1 below 0.5.

3) Generate Frequency Structure:

We generate all the frequency structures according to the chroma position candidates. For each candidate, we divide its selected positions into two non-overlapping groups. The two position groups are for the replicas of FC1 and FC2 , respectively. It is important to note that FC1 and FC2 are symmetric, i.e., swapping them does not result in a new frequency structure. Then without loss of generality, we only assume equal or conjugate replicas of a chroma, i.e., the replicas of a chroma C are all in {C, C∗}. It may produce multiple frequency structures (see Fig. 2(d)).

B. Optimize Parameters:

Following [2], we parameterize the complex color transformation matrix M as M1 + iM2, where M1 and M2 are the real and imaginary parts of M, respectively, and they are both real. Then FL, FC1 , and FC2 can be linearly parameterized by M. We apply the inverse symbolic DFT to the parameterized frequency structure and obtain the vectorized CFA pattern denoted by CM1 + DM2, where C and D are the complex coefficient matrices for M1 and M2, respectively. Let cj be the j-th channel of the RGB CFA pattern with a size of n r × nc, where j ∈ {R, G, B}. The vectorized CFA pattern is (vec(c_G), vec(cG), vec(cB)) with a size of nrnc× 3, where vec(·) is the operator to convert a matrix into a vector.

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We take the frequency structure of Hirakawa CFA [3] as an example. We first write the color transformation in (5) in more detail:

$$\begin{pmatrix} F_L \\ F_{C_1} \\ F_{C_2} \end{pmatrix} = \begin{pmatrix} M_{11}^{(1)} + iM_{11}^{(2)} & M_{12}^{(1)} + iM_{12}^{(2)} & M_{13}^{(1)} + iM_{13}^{(2)} \\ M_{21}^{(1)} + iM_{21}^{(2)} & M_{22}^{(1)} + iM_{22}^{(2)} & M_{23}^{(1)} + iM_{23}^{(2)} \\ M_{31}^{(1)} + iM_{31}^{(2)} & M_{32}^{(1)} + iM_{32}^{(2)} & M_{33}^{(1)} + iM_{33}^{(20))} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

where the superscripts (1) and (2) indicate that the elements are from M1 and M2, respectively. The conjugate of FC2 is given as:

$$F_{c_2}^* = \left(M_{31}^{(1)} - iM_{31}^{(2)}, M_{32}^{(1)} - iM_{32}^{(2)}, M_{33}^{(1)} - iM_{33}^{(2)}\right)P$$

Where P = (R,G, B)T. Then we substitute and into the frequency structure of Hirakawa CFA shown in Fig. 1(3b). We next apply the inverse symbolic DFT to the frequency structure and we have:

$$\begin{pmatrix} ((1,\ 1,\ 2)\mathrm{M}_1+(i,\ i,\ 0)\mathrm{M}_2)\mathrm{P}, & ((1,-1,-2)\mathrm{M}_1+(i,-i,0)\mathrm{M}_2)\mathrm{P} \\ ((1,-1,\ 0)\mathrm{M}_1+(i,-i,\ 2)\mathrm{M}_2)\mathrm{P}, & ((1,\ 1,\ 0)\mathrm{M}_1+(i,\ i,-2)\mathrm{M}_2)\mathrm{P} \\ ((1,\ 1,-2)\mathrm{M}_1+(i,\ i,\ 0)\mathrm{M}_2)\mathrm{P}, & ((1,-1,\ 2)\mathrm{M}_1+(i,-i,\ 0)\mathrm{M}_2)\mathrm{P} \\ ((1,-1,0)\mathrm{M}_1+(i,-i,-2)\mathrm{M}_2)\mathrm{P}, & ((1,\ 1,\ 0)\mathrm{M}_1+(i,\ i,\ 2)\mathrm{M}_2)\mathrm{P} \end{pmatrix}$$

So the vectorized CFA pattern in the RGB basis can be denoted by CM1 + DM2 with a size of 8 × 3, where

$$\mathbf{C} = \begin{pmatrix} 1 & 1 & 2 \\ 1 & -1 & 0 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \\ 1 & -1 & -2 \\ 1 & 1 & 0 \\ 1 & -1 & 2 \\ 1 & 1 & 0 \end{pmatrix} \text{ and } \mathbf{D} = \begin{pmatrix} i & i & 0 \\ i & -i & 2 \\ i & i & 0 \\ i & -i & -2 \\ i & -i & 0 \\ i & i & -2 \\ i & -i & 0 \\ i & i & 2 \end{pmatrix}$$

The produced CFA pattern in the RGB basis should be physically realizable, i.e., CM1 + DM2 is real and lies in [0, 1]. Also, the sum across color channels of CFA pattern should be an all-one matrix, i.e., the vectorised CFA pattern satisfies (CM1 + DM2)(1, 1, 1)T = 1. Accordingly, we propose the following parameter optimization model:

$$\min_M \|M^{-1}\|_2 \quad s.t\ C\Re(M) + D\Im(M) \geq 0, \left(C\Re(M) + D\Im(M)\right)a = e, \quad (12)$$

where M−1 is the inverse of M, a = (1, 1, 1)T, e = 1nrnc× 1, ≥ stands for component wise greater than or equal to, 0 denotes the zero matrix, 1 denotes the matrix whose elements are all 1, and <(·) and =(·) are the linear operators to extract the real and the imaginary parts of a complex vector or matrix, e.g., <(M) = <(M1 + iM2) = M1 and =(M) = M2. As noted in [7], the constraint (C<(M)+ D=(M))a = e in (12) is equivalent to a simpler one: Ma = b, where b = (1, 0, 0)T. So we reformulate (12) into an equivalent one:

$$\min_M \|M^{-1}\|_2 \quad s.t\ C\Re(M) + D\Im(M) \geq 0, Ma = b, \quad (13)$$

Equation part of ADMM (alternating direction method of multipliers) for multi objective optimization:-

Non linear image degraded model:

$g=s(H f_{true})+n$

Where g=Observed image

H=blurring matrix

n=noise vector

Non linear least square problem:

$\arg \underset{f}{\mathrm{Min}} \frac{1}{2} \|s(Hf)-g\|_2^2$

TV based nonlinear least square problem:

$\arg \underset{f}{\mathrm{Min}}\ E(f)\ \frac{1}{2} = \|s(Hf)-g\|_2^2 + \mu \sum_{i=1}^{m2} |\mathrm{Dif}|2$

Where μ= regularization parameter

$\sum_{i=1}^{m2} |\mathrm{Dif}|2$ = discrete total variation of f

a1≤ f ≤ a2,≤≤Dif=discrete gradient of f at i^{th} pixel

$\mathrm{Arg}\ \min \frac{1}{2} \|s(z)-g\|_2^2 + \mu \sum \|Pi\|_2 + \chi k1(u) + \chi k2(v)$

Subject to hf=z,f=u,f=v, Dif=Pi

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(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijareeie.com

Vol. 6, Issue 11, November 2017

and $\chi k1$ (u) and $\chi k2$ (v)are indicator functions given by,

$$\chi k1(u)= \begin{cases} 0, \text{ if } u-a1 \geq 0 , \\ \infty, \text{ otherwise} \end{cases} \qquad \chi k2(u)= \begin{cases} 0, \text{ if } v-a2 \geq 0 , \\ \infty, \text{ otherwise} \end{cases}$$

V. RESULTS OF EXPERIMENT

We can take any cfa model for generating the frequency structure in the mat lab there after we will specify the luma at the baseband and the remaining frequencies obtained from non zero terms by performing multi objective optimization for our required size of image. we have selected the hao model cfa with the 40% white pixels in a period

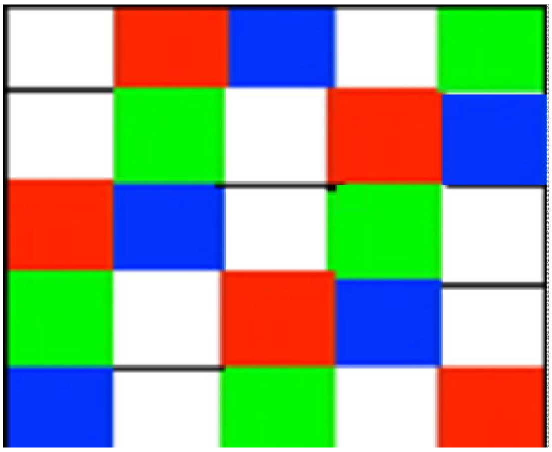


Fig 4:-used cfa(hao) to generate frequency structure

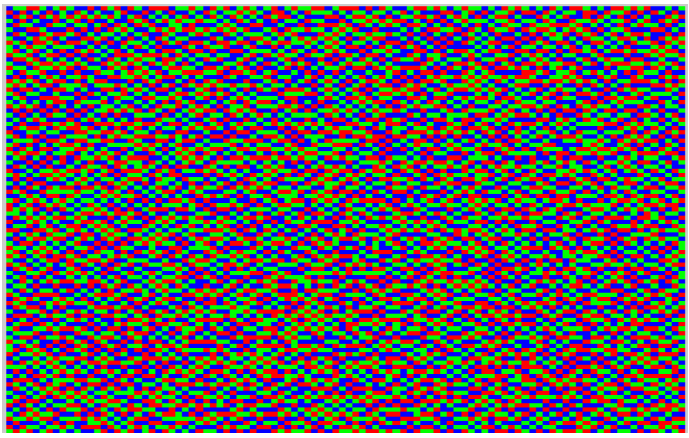
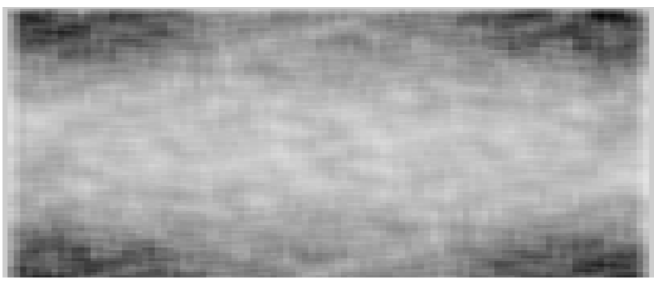
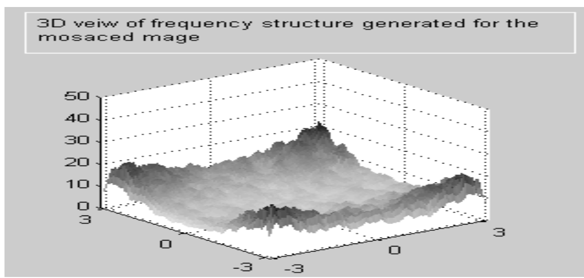


Fig 5:-color filter mosaic obtained after multi objective optimization

The above figure shows the obtained color filter of image(kod1) with the image obtained after performing multi objective optimization(where the minimum distance between luma and chroma should be maximized and the minimum distance between multiple replicas should be maximized).This not fixed model of color filter as it is optimized according to the luma chromas of the input image, so with the luma chroma variations in the input image our color filter model will change automatically for better demosacing. Now we will see how multi objective optimization has implemented n the below figure of frequency spectrum of color filter obtained



(a)



(b)

Fig:-(a)frequency spectra of the color filter array (b)3d view of frequency spectra

Luma is the area covered with white space where as chroma is the black dots at four corners
From the above figure we can see the maximum reduction of overlap among the frequency spectra of luma and chromas.We can see there is no chroma in horizontal and vertical directions of luma. With this we can reconstruct the mage with fewer visual artifacts than the remaining color filter arrays exist, for that we will calculate the peak signal to

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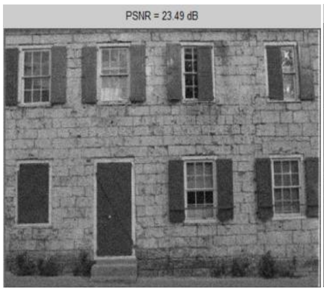
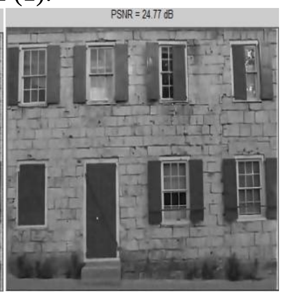
nose ratio (PSNR) for the input original image and we will compare it with the output mage peak signal to nose ratio (PSNR).

Till now the existing color filter arrays has taken the Kodak data set 24 images, which are under the format of photographic network group (.png), along with them we have tested our algorithm on standard test image of jelly been (.tiff) which is in the format of tagged image file format and the Lena (.jpg) format of joint photographic expert group.

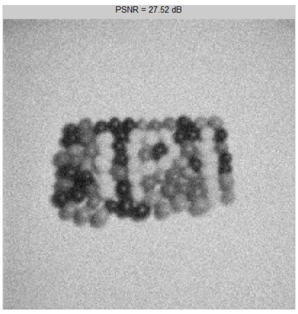
KODAK DATA SET IMAGE (1):-





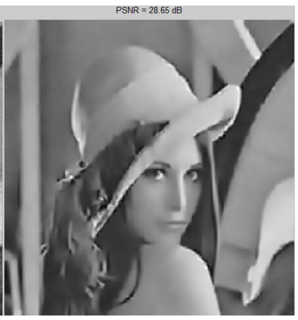
Input image **Output image**

STANDERD TEST IMAGE JELLY BEEN:-



Input image **Output image**

LENA TEST IMAGE:-



Input image **Output image**

Table of PSNR values comparison for 24 Kodak dataset Images, LENA and JELLY BEEN images

IMAGE	INPUT IMAGE PSNR VALUE	OUTPUT IMAGE PSNR VALUE
kodim01	23.51	24.81
kodim02	26.55	29.85
kodim03	26.71	30.71
kodim04	26.59	29.75
kodim05	24.42	25.29
kodim06	24.41	25.28
kodim07	26.39	30.40
kodim08	21.84	23.80
kodim09	26.23	30.23
kodim10	26.22	29.62
kodim11	25.17	27.41
kodim12	26.46	30.62
kodim13	22.08	22.60
kodim14	25.00	26.45
kodim15	26.05	29.51
kodim16	25.99	27.99
kodim17	26.37	29.50
kodim18	24.57	25.55
kodim19	24.70	27.19
kodim20	25.74	29.57
kodim21	24.77	26.71
kodim22	25.56	27.86
kodim23	26.77	32.52
kodim24	23.87	25.13
jelly	27.53	34.43
bean	26.71	30.71
lena		

VI.CONCLUSION

In this paper, we present an automatic CFA design method in the frequency domain based on the frequency structure [7]. To accomplish this, we develop a multi-objective optimization approach to automatically rule out a majority of unpromising frequency structures. Then for each frequency structure candidate, we present a new parameter optimization method that is appropriate for arbitrary frequency structures, including those with conjugate chrominance

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replicas. Our work provides an automatic approach to designing CFAs that are advantageous during the subsequent demosaicking process in producing fewer visual artifacts. Extensive experiments on standard test images demonstrate the superiority of our design method

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