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Adaptive Design of Color Filter Arrays by using the Frequency Domain Approach

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Abstract

In digital color imaging, the image is obtained by a single sensor which is extend over by a color filter array (CFA), in every pixel only single color component has to measure by using single sensor. Demosaicking is the procedure of rebuild the complete color image from a raw image. So the CFA can be effected by irreversible visual artifacts, the quality of the demosaicked images is decisive for the CFA and demosaicking algorithm. Providentially, to control these issues the CFA design in frequency domain allocates a theoretical approach. Basically, in the frequency domain all conventional methods there is an involvement of human beings. In this paper, we are introducing adaptive design of CFA in the frequency domain. In this method the mosaicked images mainly depends on the frequency structure representation. To present the frequency structure candidates we are using a multi-objective optimization, by using this overlapping between the mosaicked frequency image components with the CFA is minimized. In the constrained optimization problem each candidate parameters are optimized. The technique used to solve the optimization problem is alternating direction method (ADM). Arbitrary frequency structure is the application of parameter optimization method, including the conjugate replicas of chrominance components. The advantages of the proposed method for the benchmark images are shown in experimental results. In the future work, bilateral filter is used to improve the performance as well as quality of an image with increased SNR value.

Keywords—Color filter array (CFA), demosaicking, multi-objective optimization, alternating direction method (ADM),adaptive design.

1. Introduction

For the creation of color image we need a color filter array. In these days every camera, video camera, vision system and every scanner has a color filter array. In top of the light sensor the color filter array is fabricated. In the color filter array the filtered images will grab the energy of only one color light at every pixel this process is called as demosaicking. In [1, 2, 3] will rebuild the image with all three colors, red, green, blue at every pixel. Excluding some of the CFAs [4, 5], to fulfill the entire array of image sensors a 2-dimentional CFA normally consist of plurality of minimal repeating patterns. Different CFAs will perform different minimal repeating CFA patterns. The first CFA is introduced in 1976 by Bayer of Kodak [6]. He uses the ½ green, ¼ red ¼ blue pixels, only less CFA patterns are introduced in recent years.

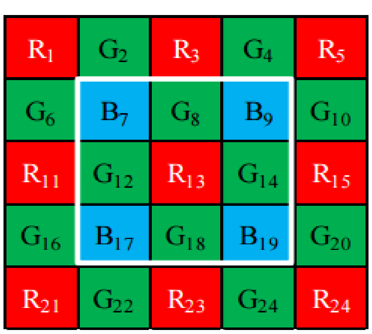

Figure 1: Bayer pattern showing the interpolation kernel – a 3x3 pixel neighborhood around the central pixel R13.

Most of the patterns are proposed for the better performance of demosaicking [7, 8, 9]. In the recent scenario for the high speed imaging high light sensitivity cameras are expected which can be used in low light environment. In the year 2007 Kodak published new generation of CFA [10] named as CFA2.0. in this ¼ green, 1/8 red and 1/8 blue pixels and ½ white pixels are used. (called as panchromatic pixels, wide-band pixels, luminance pixels).It will have the highest sensitivity and no visible spectrum energy.

Now introducing of high light sensitivity and high demosaicking performance compared to the Kodak CFA. By using the CFA design methodology [11, 12, 13] we introduce a new frequency structure of 5×5 CFA patterns to find the patterns with white (W), red (R), green (G) and blue (B) pixels. The demosaicking methods are based on the frequency domain filtering are used [14] and a universal demosaicking method i.e. generic variation approach [15], which

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will give the robust demosaicking framework to solve the optimization problem as a large sparse system of linear equations. Fourier analysis is the tool to view the demosaicking as demultiplexing [16, 17], and the reconstruction will be based on the chrominance/luminance decompositions [18-20].

2. Proposed Method

2.1. Method Overview

CFA design will be consist of two main methods which is shown in fig.2. For the CFA pattern size, to propose the frequency structure candidates we are performing multi objective optimization (the dashed part in fig.2) ,the respective frequency minimum distances are maximized (Fig. 2(b)-2(c)) among the chromas the replicate relations are specified (Fig.2(d)). To perform the correct form of CFA for every frequency structure parameters are optimized (Fig. 2(e)). The pattern size will not result in a unique frequency structure for every CFA as (see Fig. 2(d) and 2(e)). So after completion of total process we will select the best demosaicking performance compared to a training image set (Fig.2 (f)). Two steps are mentioned below.

In the CFA pattern size, in the frequency domain maximizing the minimum distances between the frequency components is equal to finding the maximized frequency point's minimum distance in frequency structure [7]. If we consider as a example of 5×5 CFA pattern, the different chroma position allocations will be 255 if we eliminate all the rows and columns of luma and the frequency structures additionally grows sufficiently. To reduce the calculation and optimization of the produced CFA is to use a fast and correct method to remove the majority of unpromising ones. In the subsequent stage missed frequency structures can't be recovered. To fulfill all the requirements we are introducing a multi-objective problem. it will be discussed in III-B. However the mathematical stability of color transformation is enhanced by directly minimizing the $\|M^{-1}\|_2$, rather then its approximation $\|M^{-1}\|_F$. Also the sum across all its channels is all-one matrix and is physically not realizable. Apart from that on frequency structures and CFA we won't make any assumptions. The model is introduced in sub section III-C and solution in appendix.

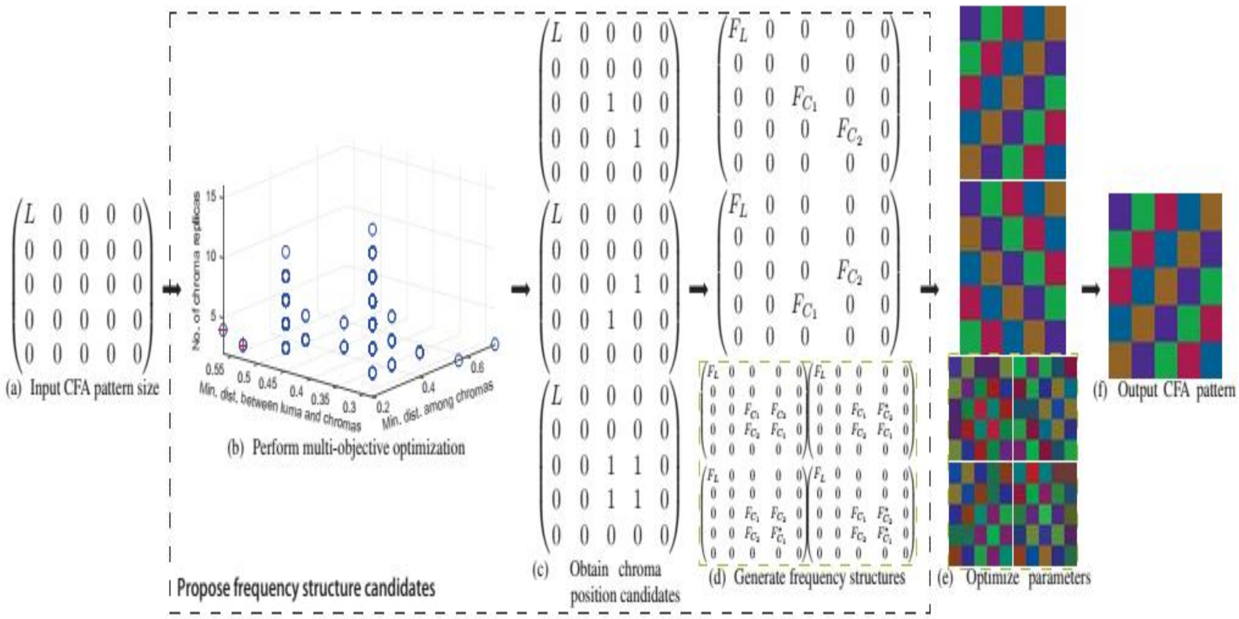

Fig.1. Overview of the proposed automatic CFA design method. From left to right: (a) is the input CFA pattern size, in which 'L' marks the position of luma and '0' marks the available chroma positions. Our method first performs multi-objective optimization (b) to obtain chroma position candidates (c), where '1' marks the selected chroma positions. Then it generates frequency structures (d) according to the chroma position candidates. It next optimizes parameters for every frequency structure to produce CFAs (e) and finally outputs the obtained CFA (f).

2.2. Propose Frequency Structure Candidates

For a CFA pattern size, the minimum distances between chromas of the frequency structures and as well as luma and chromas should be as broad as possible. The first main two objects are the horizontal and vertical axes of chroma should not locate on luma if CFA pattern is large than2×2. By combining all its estimations we can estimate each chroma adaptively [7], [24]. The third objective is the number of chroma replicas should be large as long as possible [7], the above mentioned three objects are difficult so we can not find a solution which is optimal for all the three. So we introduced a multi-objective optimization approach to find the suitable balanced solution.

1) Multi-objective Optimization: Multi-objective optimization [27] refers as same minimization and maximization of more than one objective functions. The problem is studied as follows:

$$\max_{x}\{f_1(x), f_2(x), \ldots\ldots, f_m(x)\} \quad s.t\; x \in \Omega \quad (1)$$

Totally we have m ≥ 2 objective functions $f_j$and at a time we have to maximize all the functions, x is defined as decision variable, and Ω is defined as feasible region which will a combination of various constraints. For the simplification all the objective functions has to be maximized. When the objective function f_j is minimized it's equalized as maximizing the function$-f_j$.

The objective function does not have standard measurement the example is in fig.3 values f1 ∈ [0, 30] and f2 ∈ [0, 3] have different range of values. In the objective space there is only partial ordering, so we can't compare (f1(x1), f2(x1)) T = (3, 2.5)T with (f1(x2), f2(x2))T = (2, 3)T. more often among the objective functions there may be a partial conflicts like if we maximize one function the another function values are reduced. The sum of all the objective functions is called as global objective function. But there is no chance of global objective function because of the conflicts and measurement standards. So we have to find a single solution which should be optimal w.r.t to every objective function. Pareto optimal solution is a solution for multi-objective optimization problem. The following definitions will show more information:

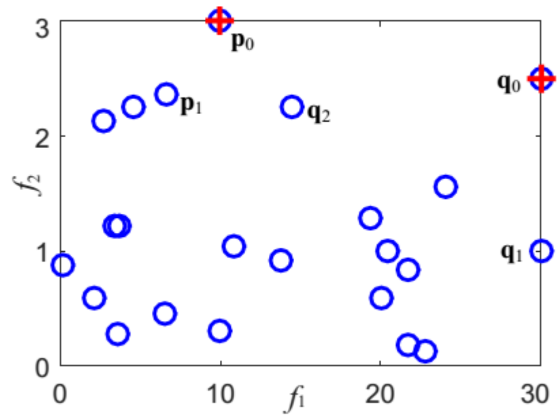

Fig.3. Solution for the multi-objective optimization problem with two objectives. blue circles indicate the feasible points and red crosses indicate the Pareto optimal solutions.

Definition 1: A decision variable $x_2$is pre-dominated by x_1 if $f_j\ (x_1) \geq f_j\ (x_2)$ for all j=1, 2…m and $f_k(x_1) > f_k(x_2)$ at least for one index.

We can take the example from fig. 3 p_0 is pre-dominated by p_1 and q_0 is pre-dominated by bothq_1 *and* q_2, but p_0 and q_0 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.

p_0, q_0 are Pareto optimal set to the multi-objective optimization solutions.

2) Obtain Chroma Position Candidates: Luma is fixed in the frequency structure (see Fig. 2(a)) at the top left frequency (0, 0) so there is no need to choose the luma. To determine the frequency structure we have to choose the replicas of the two chromas and their positions in the matrix. In the previous we already noted that the rows and columns of the frequency structure are indexed by (0, 1, · · · , $n_r - 1$) and (0, 1, …. , $n_c - 1$) and for these the frequency points are represented as $2\pi\left(0,\frac{1}{n_r},\ldots,\frac{n_r-1}{n_r}\right)$ and $2\pi\left(0,\frac{1}{n_c},\ldots,\frac{n_c-1}{n_c}\right)$ and the size of the CFA is $n_r \times n_c$. To simplify the equation 2π is removed from the frequency points. In the frequency structure if the position of the frequency points (n_x/n_c,n_y/n_r) is chosen then 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, $n_x \in$ {0, 1, …. , $n_c - 1$}, and $n_y \in$ {0, 1, ·….., n_r- 1}. When the two positions are different then it is named as conjugate position pair if two are same then it is named as self-conjugate, for example we can take (12,12), or (12,0). In the matrix if the conjugate position pairs are m_p and the self conjugate position pairs are m_s then there will be a $2^{m_p+m_s} - m_s - 1$ feasible chroma position allocations. When the size of the CFA is larger than 2× 2 then we will remove the allocations horizontal chroma positions and the vertical luma positions. On the rest of the allocations multi-objective optimization is performed.

$$\max_x \{f_1(x), f_2(x), f_3(x)\} \quad (2)$$

$s.t\ x$
$\in$ the set of feasible chroma position allocations

In the equation2 "f_1 denotes the minimum distance in between the luma and chroma positions”,” f_2 represents the minimum distances between the chroms positions” and “f_3 represents the number of chroma replicas”. In the horizontal and vertical directions the frequency structure is periodic. Here we are computing the distances between the two positions from the fig.1. For example the two positions are (x_1, y_1) and (x_2, y_2). The horizontal and vertical directions distances are $d_x = \min(x_1 - x_2|, 1 - |x_1 - x_2|)$ and $d_y = \min(y_1 -$

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$y_2|, 1 - |y_1 - y_2|$) respectively. |x| is represented as absolute value of the scalar x. then the two positions Euclidean distance is calculated as $\sqrt{d_x^2 + d_y^2}$. From equation (1) the frequency structure F_H is taken as example. In between F_L and F_{c_1}distance is taken as

$\sqrt{min(1/2\,, 1 - 1/2)^2 + min(2/4\,, 1 - 2/4)^2} = \sqrt{2}/2$ and in between F_L and $F_{c_2}^*$ distance is $\sqrt{min(1/2\,, 1 - 1/2)^2 + min(1/4\,, 1 - 1/4)^2} = \sqrt{5}/4$ and in between F_L and F_{c_2}distance is $\sqrt{min(1/2\,, 1 - 1/2)^2 + min(3/4\,, 1 - 3/4)^2} = \sqrt{5}/4$.So $f_1(F_H)$ is min (√2/2, √5/4) = √5/4.By solving the (9) we can get the Pareto optimal set from a given point set (see Fig. 3). For the Bayer CFA the objective value of f_1 is 0.5. So compared with f_2 andf_3, f_1 is more important so the chroma position candidates are rejected when the objective values of f_1 is below 0.5.

3) Generate Frequency Structure: according to the chroma position candidates the frequency structures are generated. For every candidate, the selected positions are divided into two non-overlapping groups. The two position group replicas named as f_{c_1} and f_{c_2} respectively. The main point f_{c_1} and f_{c_2} are symmetric, i.e., if we swap them we does not get any new frequency structure. So 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∗}.as shown in fig. 2(d) it may produce multiple frequency structures.

2.3. Optimize Parameters

The complex color transform matrix M is parameterized as $M_1 + iM_2$, where M_1 and M_2 are real and imaginary parts of M, but they both are indicated as real. Then F_L, F_{C_1} and $F_{C_2}$are linearly parameterized by M. Now inverse symbolic DFT to the parameterized frequency is applied to obtain the vectorized CFA pattern as $CM_1 + DM_2$, where C and D are denoted as complex coefficient matrices for M_1 and M_2. Let c_j be the j-th channel of the RGB CFA pattern with a size of $n_r \times n_c$, where $j \in \{R, G, B\}$.Then the vectorized CFA pattern is defined as $(vec(c_R), vec(c_G), vec(c_B))$ with a size of $n_r n_c \times 3$. As shown in above $vec(\cdot)$ is the operator to convert a matrix into vector. Let the frequency structure of Hirakawa CFA [14] be taken as example. Thus, the color transformation in is defined as:

$$\begin{pmatrix} F_L \\ F_{C_1} \\ F_{C_2} \end{pmatrix} = \begin{pmatrix} M_{11}^{(1)} + iM_{11}^{(2)} & M_{12}^{(1)} + iM_{12}^{(2)} & M_{13}^{(1)} + iM_{13}^{(2)} \\ M_{21}^{(1)} + iM_{21}^{(2)} & M_{22}^{(1)} + iM_{22}^{(2)} & M_{23}^{(1)} + iM_{23}^{(2)} \\ M_{31}^{(1)} + iM_{31}^{(2)} & M_{32}^{(1)} + iM_{32}^{(2)} & M_{33}^{(1)} + iM_{33}^{(2)} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (3)$$

Hence, the conjugate of F_{C_2} is given as

$$F_{C_2}^{*} = (M_{31}^{(1)} - iM_{31}^{(2)}, M_{32}^{(1)} - iM_{32}^{(2)}, M_{33}^{(1)} + iM_{33}^{(2)})\boldsymbol{P} \quad (4)$$

Where $P = (R;\ G; B)^T$. Then we substitute (10) and (11) into the frequency structure of Hirakawa CFA shown in Fig. 1(3b). We next apply the inverse symbolic DFT to the frequency structure.

So the vectorized CFA pattern in the RGB basis can be denoted by $CM_1 + DM_2$ with a size of 8×3.

The produced CFA pattern in the RGB basis should be physically realizable, i.e., $CM_1 + DM_2$ 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 vectorized CFA pattern satisfies$(CM_1 + DM_2)(1,1,1)^T = 1$.

3. Simulation Results

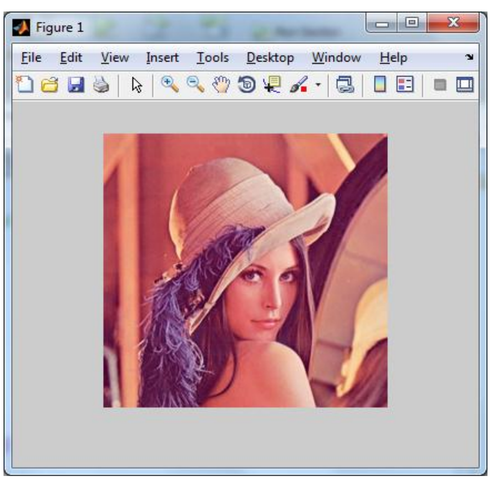

Fig.4. original image

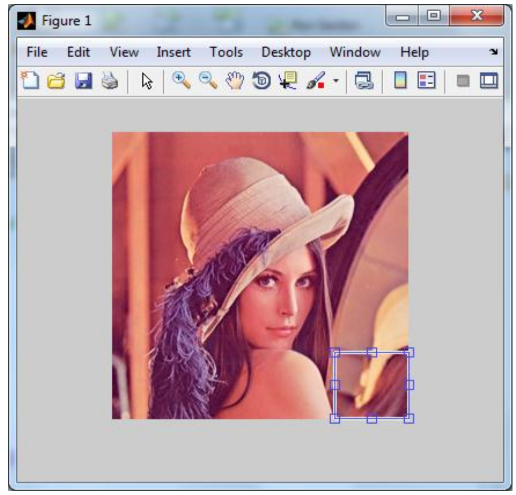

Fig.5. crop the particular region of an image to denoise.

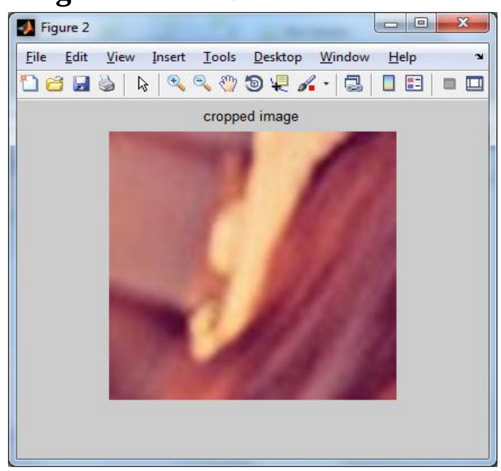

Fig.6. Cropped image.

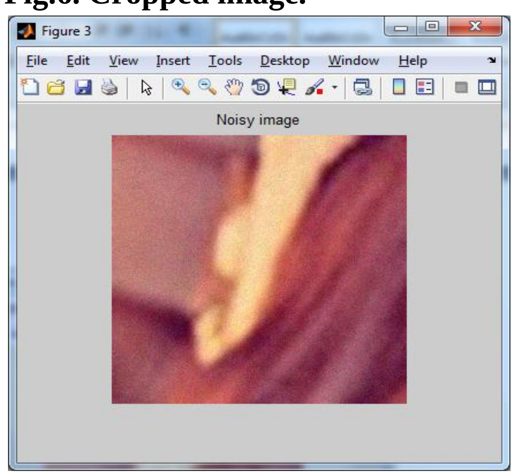

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Fig.7. Noisy image.

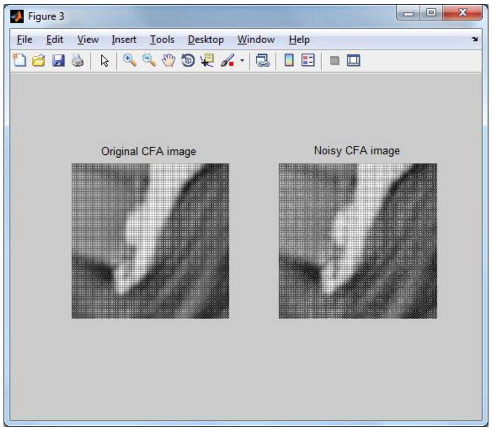

Fig.8. Apply CFA to the cropped original and noisy image.

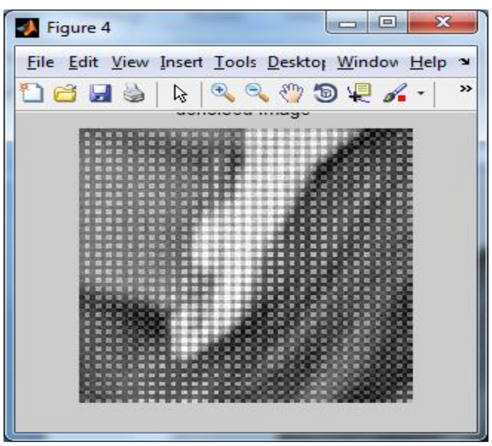

Fig.9. Denoised image

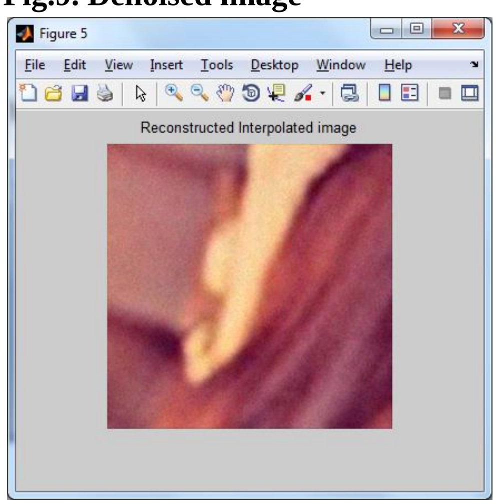

Fig.10. Reconstructed denoised color image

4. Extension Results

Bilinear interpolation is used to find the new pixel value by using the neighboring pixel values. It is a resampling method which uses the distance weighted average of the four nearest pixel values. The output cell center is found by using the nearest four cell center input weights based on the distances and then averaged. Interpolation is the process used to generate the original point which is unknown. The performance of SNR is **better in bilinear interpolation compared to bayes technique.**

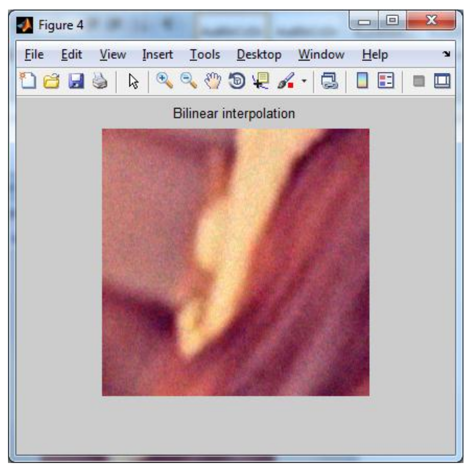

Fig.11. Extension result of bilinear interpolation

5. Conclusion

In this paper, based on the frequency structure we are presenting an automatic CFA design method in the frequency domain. To find the unpromising frequency structures automatically we find a solution i.e. multi-objective optimization approach. A new parameter optimization is introduced for each frequency structure candidate which should be appropriate for the arbitrary frequency structures, including the conjugate chrominance replicas. In generating the fewer visual artifacts in the process of subsequent demosaicking process the proposed CFA design will provide automatic results. In the extensive experiment results we can see the output the superior proposed method.

6. REFERENCES

[1] B. K. Gunturk, J. Glotzbach, Y. Altunbasak, R. W. Schaffer, and R. M. Mersereau, "Demosaicking: Color filter array interpolation," IEEE Signal Processing Mag., vol. 22, pp. 44–54, Jan. 2005.

[2] D. Alleyson, S. Susstrunk, and J. Herault, "Linear demosaicing inspired by the human visual system," IEEE Trans. Image Processing, vol. 14, pp. 439–449, Apr. 2005.

[3] O. Losson, L. Macaire, and Y. Yang, Comparison of Color Demosaicing Methods, vol. 162, chapter 5 in Advances in Imaging and Electron Physics, pp. 173–265, 2010.

[4] W. Zhu, K. Parker, and M.A. Kriss, "Color filter arrays based on mutually exclusive blue noise patterns," J. Vis. Commun. Image Represent., vol. 10, no. 3, pp. 245–267, Sept. 1999.

[5] L. Condat, "A new random color filter array with good spectral properties," in Proc. IEEE Internat. Conf. Image Process., Nov. 2009.

[6] B.E. Bayer, "Color imaging array," US Patent 3 971 065, 1976.

[7] R. Lukac and K.N. Plataniotis, "Color filter arrays: design and performance analysis," IEEE Trans. Consumer Electron., vol. 51, no. 4, pp. 1260–1267, Nov. 2005.

[8] K. Hirakawa and P.J. Wolfe, "Spatio-spectral color filter array design for optimal image recovery," IEEE Trans. Image Processing, vol. 17, pp. 1876–1890, Oct. 2008.

[9] L. Condat, "A new color filter array with optimal sensing properties," in Proc. IEEE Internat. Conf. Image Process., Nov. 2009.

[10] J. Compton and J. Hamilton, "Image sensor with improved light sensitivity," US Patent 20 070 024 031A1, 2005.

[11] Y. Li, P. Hao, and Z. Lin, "Color filter arrays: representation and analysis," Tech. Rep. RR-08-04, Dept. of Computer Science,

Queen Mary, Univ. of London (QMUL), 2008.

[12] Y. Li, P. Hao, and Z. Lin, "Color filter arrays: a design methodology," Tech. Rep. RR-08-03, Dept. of Computer Science, Queen Mary, Univ. of London (QMUL), 2008.

[13] P. Hao, Y. Li, Z. Lin, and E. Dubois, "A geometric method for optimal design of color filter arrays," IEEE Trans. Image Processing, in press, 2011.

[14] E. Dubois, "Frequency-domain methods for demosaicking of Bayer-sampled color images," IEEE Signal Processing Lett., vol. 12, pp. 847–850, Dec. 2005.

[15] L. Condat, "A generic variational approach for demosaicking from an arbitrary color filter array," in Proc. IEEE Internat. Conf. Image Process., Nov. 2009.

[16] D. Alleysson, S. S¨usstrunk, and J. H´erault, "Linear demosaicing inspired by the human visual system," IEEE Trans. Image Process., vol. 14, no. 4, pp. 439–449, Apr. 2005.

[17] E. Dubois, "Filter design for adaptive frequency-domain Bayer demosaicking," in Proc. IEEE Internat. Conf. Image Process., 2006, pp. 2705–2708.

[18] B. K. Gunturk, Y. Altunbasak, and R. M. Mersereau, "Color plane interpolation using alternating projections," IEEE Trans. Image Process., vol. 11, no. 9, pp. 997–1013, Sept. 2002.

[19] L. Zhang and X. Wu, "Color demosaicking via directional linear minimum mean square-error estimation," IEEE Trans. Image Process., vol. 14, no. 12, pp. 2167–2178, Dec. 2005.

[20] K. Hirakawa, X.-L. Meng, and P. J. Wolfe, "A framework for waveletbased analysis and processing of color filter array images with applications to denoising and demosaicing," in Proc. IEEE Internat. Conf. Acoust. Speech Signal Process., 2007, vol. 1, pp. 597–600.