Demosaicing Algorithm for Color Filter Arrays Based on SVMs

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Abstract

One color filter array (CFA) used in a digital camera allows only one of the red-green-blue primary color components to be sensed at each pixel, and interpolating the other missing two components by methods known as demosaicing. A novel support vector machines (SVMs) based demosicing algorithm is proposed to reduce edge artifacts and false color artifacts effectively. The proposed algorithm is a four-step method. Firstly, construct middle plane K_r or K_b on the mosaic image. Secondly, train SVMs with the trained samples constructed on the middle plane. Thirdly, interpolate the unknown value of the middle plane K_r or K_b. Finally, calculate the missing pixel value. Experimental results showed that the proposed approach produced visually pleasing full-color result images and obtained better PSNR values than other demosaicing algorithms

Keywords: *Demosaicing, Color filter array (CFA), Image interpolation, Support vector machines (SVMs).*

1. Introduction

In recent years, rapid research and development have helped make digital imagers more and more widespread in daily life. People's requirements to the image quality are more rigorous. The different processing strategies implemented in image sensors, and the different stages of image processing are more important. Demosaicing is one of the significant stages of image processing.

To capture a color image, three image sensors are needed to simultaneously sense the three-primary colors: red (R), green (G) and blue (B). However, to minimize the size, cost and complexity, designers employ a single image sensor overlaid with a color filter array (CFA) to acquire the color image. With this scheme, only one pixel value of the three-primary colors is sensed. To restore a full-color image, the two missing color values at each pixel need to be estimated from the adjacent pixels. This process is commonly known as CFA interpolation or demosaicking.

Bilinear interpolation is the simplest method for CFA interpolation, in which the missing color value is filled with the average of its neighboring CFA samples in the same color. It introduces errors in the edge region with blurred result images and produces color artifacts. To obtain more accurate and visually pleasing results, many sophisticated CFA interpolation methods have been proposed. In [1] an effective color interpolation algorithm (ECI) using signal correlation to get better image quality is provided. The frequency response of this approach is better than the conventional methods especially in high frequency. Another enhanced ECI interpolation approach (EECI) which effectively used both the spatial and the spectral correlations is proposed in [2], and it provided effective scheme to enhance two existing state-of-the-art interpolation methods. In [3] a universal demosaicking algorithm (UD) is provided employing an edge-sensing mechanism and a post-processor to unify existing interpolation solutions. Tsai and Song [4] exploited high-frequency information of the green channel to reduce the aliasing error in red and blue channels. In [5], Lian et al designed an efficient filter for estimating the luminance at green pixels and presented an adaptive filtering approach to estimating the luminance at red and blue pixels. Hos et al designed several new CFA patterns based on the ideal of minimizing the demosaicing error [6], and used the adaptive weighting method to get full color image. A SVMs based error correction scheme is provided in [7] to improve interpolation accuracy of result images. Recently, a novel SVMs based image interpolation method for gray images employed the local spatial property information is proposed in [8], and experimental data showed that SVMs based interpolation can provide high quality interpolation result images. In this paper, SVMs based interpolation is used for demosaicing.

The remainder of this paper is organized as follows. In section 2, SVMs is briefly introduced. In section 3, the details of the proposed demosaicing approach is described. Section 4 is the experimental results of the methods under comparison. Finally, conclusion is given in section 5.

2. SVMs

SVM is built on the basis of statistical learning theory with optimal ways to solve the problem of machine learning. Which have been used successfully for many supervised classification tasks, regression tasks and novelty detection tasks [9-12]. Support vector regression (SVR) is a function approximation approach applied with SVM. A wide range of image processing problems have also been solved with

SVMs. The basic idea of SVR is mapping the data in the current space with linear non-separable case to a high dimensional feature space in which the data point is separable. A training data set $T=\{(x_i, y_i)\}_{i=1}^{m}$ consists of m points $\{x_i, y_i\}$, $i=1,2,...,m$, $x_i \in R^d$, $y_i \in R^d$, where, x_i is the i-th input pattern and y_i is the i-th output pattern. The aim of SVR is to find a function $f(x)=<\omega,\phi(x)>+b$ to obtain eventual targets y corresponding x.

The kernel function $k(x_i,x)=<\phi(x_i),\phi(x)>$ is used to implement the nonlinear mapping, which can be selected as linear kernel, polynomial kernel, radial basis function (RBF) kernel, or two layer neural kernel.

3. Proposed Algorithm

The most popular CFA filter pattern is Bayer pattern in which the color components are placed in an orderly fashion as showed in Fig 1 [1-3]. Although other patterns can also be processed with our proposed algorithm, Bayer pattern is regarded as the default CFA pattern in our algorithm description.

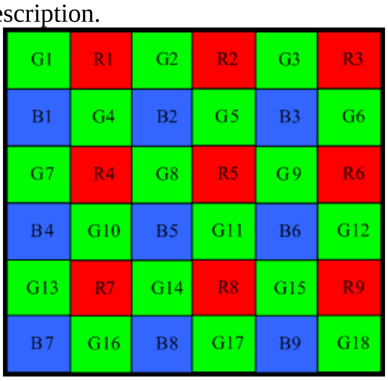


Fig.1 Bayer pattern of CFA

Image interpolate rely heavily on color correlations, which include spatial and spectral correlations. The image spectral correlation between the R, G, B channels can be represented as K_r plane and K_b plane, where $K_r=G-R$ and $K_b=G-B$ [1]. For real-world images, the contrasts of K_r and K_b are quite flat over small regions, and this property is suitable for interpolation.

The SVM-based interpolation is performed to G channel, B channel and R channel respectively. Four steps are needed when interpolating an unknown pixel value no matter in which channel. We summarize the procedure as follows.

(1) Construct middle plane K_r or K_b on the mosaic image.

(2) Train SVM with trained samples constructed by the known values on the K_r plane or K_b plan.

(3) Interpolate the unknown values of the K_r plane or K_b plane using the trained SVM.

(4) Calculate the unknown pixel value using the interpolated K_r or K_b values.

When using SVMs, the samples are constructed by selecting the neighbor pixels. The principle of selecting neighbor pixels region is the trained mode similar with the forecast mode. The forecast mode is determined by the position of the same color pixels around the neighbor regions.

Firstly, interpolate G channel.

Step1: Interpolate the G color value with known R.

(1) The plane of K_r is constructed for SVMs training.

We can calculate K_r value for the pixels with known G color value employing the two adjacent known R color values. Fig 1 shown, pixel G_3 is in the place of odd row, the corresponding K_r value can be calculated with $K_{r3}=G_3-(R_2+R_3)/2$. Pixel G_5 is in the even row, the corresponding K_r value can be calculated wit $K_{r5}=G_5-(R_2+R_5)/2$. For the special brim column or row pixels, for instance, G_{13} and G_{16}, we can obtain the corresponding K_r value with $K_{r13}=G_{13}-R_7$ and $K_{r16}=G_{16}-R_7$, respectively. After the K_r plane for all the pixels with known G color value is estimated, as shown in Fig 2, this K_r plane can be used for SVMs training.

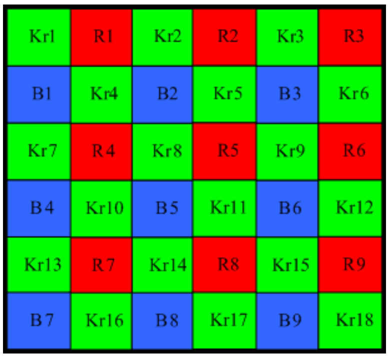


Fig.2 Kr plane for G channel interpolate

(2) Interpolate the K_r values of the pixels with known R in the K_r plane using SVMs.

Every pixel with known K_r value in the above K_r plane is selected as center pixel to construct three samples for SVMs training. Output patterns of these samples are the K_r values of the center pixel. The input pattern is the four-dimensional vector constituted by the K_r values of four neighbor pixels around the center pixel. For example, K_{r8} is selected as center pixel, one input pattern can be comprised of K_{r2}, K_{r7}, K_{r14} and K_{r9}. Another input pattern constituted by K_{r4}, K_{r10}, K_{r11} and K_{r5}. The third pattern is made up of K_{r1}, K_{r13}, K_{r15} and K_{r3}. All these samples are used for SVMs training. The trained SVMs can be employed to estimate K_r value of the pixel with known R color value. For example, when the input pattern constituted by K_{r5}, K_{r8}, K_{r11} and K_{r9} is used, K_{r5}corresponding R_5 can be obtained with the trained SVMs.

(3) For the pixel i with known R color value the G color value is estimated as $G_i = K_{ri} + R_i$

Step2: Interpolate the G color value with known B.

Likewise, the plane of K_b can be constructed, and all the K_b values of the pixels with known B color value can be estimated with SVMs. Then, the G color value of the pixel i with known B color value can be estimated with $G_i = B_i + K_{bi}$. Now, we can obtain all G color value of the image, which can be considered as the known pixels in the second pass.

Secondly, interpolate B channel.

Step1: Interpolate the B color value with known R.

Similarly with the work in G channel, the plane of K_b can be constructed for SVMs training. The K_b value of the pixel i with known B color value can be calculated as $K_{bi} = G_i - B_i$, where G_i has been estimated in the first pass. And we get the K_b plane showed in Fig 3. In this plane, SVMs are trained with the samples constructed from pixels with known K_b value. K_b value of the center pixel is the output pattern for the samples. Two input patterns of the center pixel can be used to construct samples for SVMs training. For example, when K_{b5} is selected as the center pixel, one of the two input patterns is constitutive of K_{b1}, K_{b7}, K_{b9} and K_{b3}, Another one is comprised of K_{b2}, K_{b4}, K_{b8} and K_{b6}. After all the examples are used for SVMs training, the trained SVMs can be used to estimate K_b value of the pixel with known R color value. For example, K_{b5} corresponding G_{r5}/R_5 can be estimated with trained SVMs employing the input pattern constituted by K_{b2}, K_{b5}, K_{b6} and K_{b3}. Thus, all the K_b values of the pixels with known R color value can be estimated.

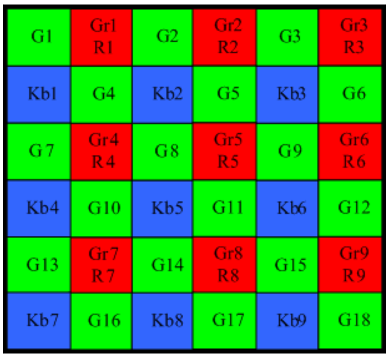


Fig.3 Kb plane for B channel interpolate

Step2: Interpolating the B color value with known G.

So far, all the rest pixels with unknown K_b values in K_b plane are the pixels with known G color values. These unknown K_b value can also be estimated using the trained SVMs. For examples, K_{b9} corresponding G_9 can be estimated with the input pattern constructed from K_{b3}, K_{b5} (corresponding G_{r5}/R_5), K_{b6} and K_{b6} (corresponding G_{r6}/R_6). Then the B color value of the pixel i could be calculated with $B_i = G_i - K_{bi}$. Now, we get the B color channel of the image.

Thirdly, interpolate R channel just like the interpolation to B channel.

4. Experiments

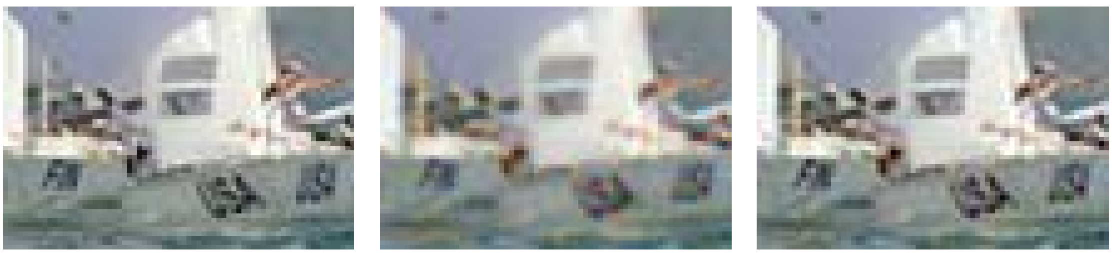
The experiments are performed in Matlab 2G memory, 3.0GHz single-core CPU and the SVM tools for Matlab [12] are used. In order to verify the effect of the proposed algorithm, some standard test images that have been widely used in other literatures and a wide range of real images are used in our experiments. Some of these test images are showed in Fig 4. Bilinear interpolation, ECI interpolation [1], EECI interpolation [2], UD interpolation [3], Hos et al. [6] (CFA4b Adaptive), and our proposed approach are used in our experiments. In these experiments, the γ-SVR with radial basis function kernel is employed for the SVMs based interpolation, and all parameters in the SVMs tool are set to default. Peak signal to noise ratio (PSNR) value between the source image and the result image is employed to compare different demosaicing algorithms. PSNR is calculated for all the images showed in Fig 4 and listed in Table 1. It is obvious that the proposed approach gets the highest average PSNR value. Hos's algorithm [6] obtained high PSNR of the image Sails, Mountain, and Sky. The common characteristic of the three images are with fewer edges.

Experimental result images of image Sailboat employing different demosaicing approaches are zoomed and illustrated in Fig 5. It can be observed that the ECI interpolation blur the image edges with visible artifacts appeared in the edge regions, such as sail edge. Color artifacts are also appeared obviously in the people region and sailboat mark word region in the result images of EECI, UD and Hos's algorithm. Our proposed SVMs based approach obtains the best visual result with less edge artifacts and less color artifacts. These observation results are consistent with PSNR value listed in Table 1. Experimental result images of real image Family are illustrated in Fig 6. We can also find edge artifacts and color artifacts appeared in the result images of ECI, UD, EECI and Hos's algorithm, especially in the house edge region. The proposed approach produces less edge artifacts and less color artifacts. These observations indicate that our proposed approach keeps the edge details effectively and produces less color artifacts.

Table.1: PSNR of different demosaicing approachs

Image	ECI	EECI	UD	[6]	Proposed
Wall	26.15	25.33	25.83	29.13	**29.57**
House	26.04	28.57	28.86	31.06	**31.35**
Building	20.92	22.25	22.91	24.39	**24.51**
Face	18.13	19.13	16.89	19.99	**20.30**
Sails	24.02	26.10	26.02	**26.97**	26.81
Girl	25.40	27.40	27.43	28.44	**28.57**
Lighthouse	23.67	25.02	24.12	26.24	**26.60**
Sailboat	22.54	22.92	22.97	25.90	**26.02**
Plane	20.12	27.10	26.15	27.32	**27.56**
Mountain	22.90	24.46	24.98	**27.99**	27.86
Tree	20.89	21.88	20.21	22.19	**22.67**
Bridge	20.94	23.39	23.36	26.03	**26.15**
Sky	26.64	28.04	31.23	**33.42**	33.03
Family	21.92	23.63	25.47	27.34	**27.53**
Average	22.88	24.66	24.75	26.89	**27.04**

Fig.4 Some test images



(a) Standard image (b) ECI (c) EECI

(d) UD (e) [6] (f) Proposed

Fig.5 Zoomed region of the demosaiced image Sailboat

(a) Standard image (b) ECI (c) EECI

(d) UD (e)[6] (f) Proposed

Fig.6 Zoomed region of the demosaiced image Family

5. Conclusions

Based on the insights gained from our study, SVMs can ensure the accuracy of the interpolation results by its properties of global optimal and generalization ability, the mosaic image can be interpolated effectively with the combination of image correlation and SVMs. The proposed demosicing algorithm can reduce edge artifacts and false color artifacts effectively, have excellent effect to the image with more edge. The experimental results show that the proposed algorithm obtains higher PSNR value and produces visually pleasing full-color images.

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References

[1] S. C. Pei, I. K. Tam, “Effective Color Interpolation in CCD Color Filter Array Using Signal Correlation”, IEEE Trans.on Circuits and Systems for Video Technology, vol. 13, no. 6, 2003, pp. 503-513.
[2] L. L. Chang, Y. P. Tan, “Effective Use of Spatial and Spectral Correlations for Color Filter Array Demosaicking”, IEEE Trans. on Consumer Electronics, vol. 50, no. 1, 2004, pp 355-365.
[3] R. Lukac, K. N. Plataniotis, “Universal Demosaicking for Imaging Pipelines with an RGB Color Filter Array”, Pattern Recognition, vol. 38, no. 11, 2005, pp. 2208-2212.
[4] C. Y. Tsai, K. T. Song, “A New Edge-adaptive Demosaicing Algorithm for Color Filter Arrays”, Image and Vision Computing, vol. 25, no. 9, 2007, pp. 1495-1508.
[5] N. X. Lian, L. Chang, Y. P. Tan, V. Zagorodnov, “Adaptive Filtering for Color Filter Array Demosaicking”, IEEE Trans. on Image Processing, vol. 16, no. 10, 2007, pp. 2515-2525.
[6] P. W. Hao, Y. Li, Z. C. Lin, E. Dubois, “A Geometric Method for Optimal Design of Color Filter Arrays”, IEEE Trans. on Image Processing, vol. 20, no. 3, 2011, pp 709-722.
[7]J. Wang, L. Ji, “Image Interpolation and Error Concealment Scheme Based on Support Vector Machine”, Journal of Image and Graphics, vol. 7(A), no. 6, 2002, pp. 558-564.
[8] L. Y. Ma, Y. Shen, and J. C, Ma. “Local Spatial Properties Based Image Interpolation Scheme Using SVMs”, Journal of Systems Engineering and Electronics, vol. 19, no. 3, 2008, pp. 618-623.
[9] N. Y. Deng, Y. J. Tian, “A Novel Data Mining Method: SVM”, Science Press, Beijing, 2004.
[10] S. Zheng, J. W. Tian, and J. Liu, “Research of SVM-based Image Interpolation Algorithm Optimization”, Journal of Image and Graphics, vol. 10, no. 3, 2005, pp. 338-343.
[11] H. Z. Wang, R. Zhang, F. K. Liu etc, “Improved Kriging Interpolation Based on Support Vector Machine and Its Application in Oceanic Missing Data Recovery”, Proc. of the 2008 International Conference on Computer Science and Software Engineering, vol.4, 2008, pp. 726-729.
[12] K. S. Ni, T. Q. Nguyen. “Image Super-resolution Using Support Vector Regression”. IEEE Trans. on Image Processing, vol. 16, no. 6, 2007, pp. 1596-1610
[13] C.-C. Chang and C.-J. Lin, LIBSVM: a library for support vector machines, 2001. Software available at http://www.csie.ntu.edu.tw/~ cjlin /libsvm.

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