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ORIGINAL ARTICLE

Color image demosaicing using sparse based radial basis function network

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Abstract Images contain three primary colors at each pixel, but single sensor digital cameras capture only one of the primary channels. Process of color image reconstruction by finding the missing color component is called color image demosaicing. Various approaches have been proposed in this field of image demosaicing such as interpolation based and frequency based approaches due to sharp image edge and higher color saturation, and these techniques fail to reconstruct image efficiently. To overcome this, in this work we propose a new approach, sparse based RBF network for color image demosaicing. According to this approach a sparse model is constructed first and based on that weights are computed which are used to minimize the reconstruction error. To improve this we use optimal weight computation and RBF training for missing color component value prediction. Proposed method is implemented using MATLAB tool and experimental results show the efficiency of the proposed work in terms of color peak signal to noise ratio (CPSNR). Simulation results show 16.20% improvement in the performance in terms of CPSNR.

1. Introduction

In last decade, uses of images and videos have been grown rapidly in daily life scenarios. These images are captured using digital cameras. Since mid-1990s, digital cameras being used for consumer level applications. In today's scenario various cameras are available such as point-and-shoot which have capacity over 8 million pixels; similarly, other commercial cameras also present with capacity more than 12 million pixels. Image quality of these cameras depends on resolution, sensor's dynamic range and sensitivity of light. Various operations are performed during capturing the image such as focus adjustment, adjustment of white balance, and image compression. During the image capturing intensity of the light is sampled by using a single CMOS sensor and similarly color images are acquired in the same way but the intensity variations of light are measured in different band of colors which are red band, green band and blue band. In color image capturing process splitting of beam can be implemented which helps to measure each color at each value of image pixel, but due to computational complexity and cost raising issues it is difficult to implement for commercial and general purpose.

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This becomes a challenging task for the researchers, and to overcome this color filter array (CFA) is proposed which captures color images using single sensor. This is a process of reconstruction of full-resolution by using data of CFA. It is defined as the combinational array of alternate color filters which performs sampling on a single color band at location of each pixel. Widely used CFA pattern is displayed in Fig. 1 which is called Bayer pattern. According to this pattern red and blue filters are placed in an alternate location of pixel in horizontal and vertical directions whereas green filters are placed in quincunx way at the remaining location of the pixels.

These patterns are used to reconstruct the color image. The process of estimation of missing two values is denoted as image demosaicing. Due to the presence of single color channel, interpolation of channels must be performed with the help of spectral correlation of neighboring color components [1]. Color image reconstruction quality depends on the used template for CFA and approach for demosaicing. In this context of color image reconstruction, various approaches have been proposed by the researchers to improve the color image reconstruction quality. Demosaicing approaches are classified into the following sub-categories: (a) Spatial domain approaches [2], (b) frequency domain based demosaicing [3], (c) chrominance channel interpolation [4] and (d) post-processing technique [5].

According to spatial domain demosaicing, missing values in green channels are interpolated using heuristic approach. This approach uses computation window such as 3×3 or 5×5 with second order gradient of chrominance value. According to frequency domain approach, in order to reconstruct G channel, a low pass filter is applied. In interpolation based approaches, pixel values of G channel are interpolated in an iterative way along with horizontal and vertical directions. In post-processing techniques, median filtering based approach is implemented to compute the difference between color pixel values to estimate the missing color component. But these approaches face challenges in terms of image reconstruction quality which is evaluated by computing CPSR.

To overcome all these issues related to image demosaicing, here in this work we propose sparse based RBF network construction to perform the demosaicing. According to this approach, input image is downsampled or normalized, and this downsampled image is used to construct the sparse image model. Furthermore to optimize this, we use RBF network construction by applying optimal weight prediction and computation.

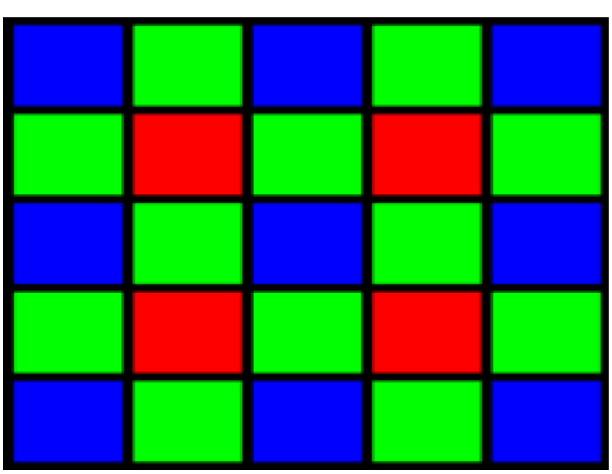

Figure 1 Bayer pattern.

Remainder of this manuscript is organized as follows: Section 2 describes the most recent related works in this field; proposed model is described in Section 2.1. Experimental study of proposed work is presented in Section 2.2 and finally conclusion is explained in Section 4.

2. Related work

This section describes about the other approaches which have been proposed by other researchers for color image demosaicing. As previous section describes about the interpolation based scheme for image demosaicing, based on this approach, Ye et al. [24] proposed a new approach based on the iterative method of residual interpolation. This approach shows more efficient outcomes when compared to residual based approach. One of the promising technique was proposed in [6] by Khashabi. This demosaicing is based on the machine learning technique. Performance of this was carried out by applying this on a publicly available dataset with ground truth. In this approach image modeling is introduced such a way that it performs better when noise is present in the image. This modeling is completed using machine learning methods which improve the performance in terms of PSNR and structural similarity. Another approach based on machine learning is presented in [7]. In this technique wavelet sub-band theory is used which improves the quality of color filter array (CFA).

Several Color image demosaicing algorithms have been proposed which require a reference image or ground-truth image. In [10,11], reference image based methods are discussed for image demosaicing. Lu et al. [9] proposed interpolation based scheme for demosaicing which consists of two steps. First step is to perform interpolation and second step is to perform post-processing. In order to overcome this, a new approach has been proposed in [8]. This work concentrates on two algorithms, in first algorithm, edge slope measurement, image sharpness and edge reconstruction accuracies are measured, in second algorithm, false color measurement, deviation estimation, color difference models and reconstruction for each channel is estimated. Lukac et al. [12], proposed an approach for image demosaicing using *PCA* (Principal Component Analysis). According to this approach, input image is zoomed first and then demosaicing is carried out. At this stage of processing, other algorithms for zooming and demosaicing can be utilized directly, but this approach faces challenge during zooming or demosaicing when performed separately, and at this time raw sensor data cannot be used effectively which results in low reconstructed image. According to CFA pattern, more information of image is stored in green channel of input image compared to other channels; half of the pixels in Bayer pattern are allocated in green channel. Detailed information can be extracted from the channel without aliasing effect on image. Main challenge is related to alignment of the pixels based on the regular distance which affects the correlation between channels [13]. Simplest method for image demosaicing is to fill the missing pixel values of each channel by applying bilinear or bicubic interpolation method [14]. Another approach based on interpolation scheme is presented by Daisuke et al. [26]. In this approach residual is computed and missing pixel values are estimated with the help of gradient based threshold image demosaicing. These discussed algorithms provide better results when the region is homogenous in nature. Key challenges faced by the researchers are artifacts, blurring at the edge of the image. These drawbacks motivate us to propose a new approach for color image demosaicing by preserving the information of the image during reconstruction.

In order to overcome this, interpolation based improved algorithms have been proposed. The key component of these methods is to preserve the edge and texture by estimating the missing color components using interpolation techniques [15,16]. Similarly, in [17] Zhang et al. proposed directional linear minimum mean square error estimation (DLMMSE) by using soft direction decision method. This approach uses horizontal and vertical color difference to compute the optimal missing value solution. As we discussed earlier that these approaches induce artifacts in the image, to overcome these artifacts Huang et al. [18] presented a filtering based image demosaicing scheme. For edge estimation in various direction and accuracy, in this approach green channel sampled data is treated as a diagonal interlaced green plane form and spatial deinterlacing is applied, which results in edge estimation. Moreover, median filtering is applied to suppress visual artifacts i.e. zipper effect, false color and interpolation.

In [27], Bach et al. proposed non-local modeling for sparse representation for color image demosaicing. This method concentrates on dictionary based learning and for restoration of image, non-local mean is applied.

2.1. Proposed model

Proposed approach for Color image demosaicing is described in this section. Proposed model is constructed using two main approaches: (a) sparse demosaicing and (b) adaptive sparse demosaicing.

According to this method, sparse demosaicing encoders are constructed and then RBF neural network based training approach is applied for adaptive approach for demosaicing.

2.1.1. Sparse demosaicing

Sparse demosaicing encoders are used to pre-train the layers of a deep neural network, which reduces the complexity of the system by avoiding the training of the network from scratch. Generally, these encoders are connected in a series and the deep network is formed by feeding the output activation function of one encoder to the input of the next encoder. In order to train the network, activation functions are computed for both clean and noisy input data.

Here input data is given as $a \in I^D$ and artifact data is given as $n \in I^D$, for this feed-forward function can be defined as

$$\begin{aligned} \mathcal{h}(x) &= f(\mathcal{W}\imath + \alpha) \\ \mathcal{y}(x) &= g(\mathcal{W}'\mathcal{h} + \alpha') \end{aligned} \tag{1}$$

$\mathcal{h}(x)$ is the hidden node activation function and $\mathcal{y}(x)$ is the reconstruction function. $f(.)$ denotes encoding and $g()$ denotes decoding of the input data. $\mathcal{W}$ is the weight of input data and α is the bias during encoding and $\mathcal{W}'$ is the weights of input data and α' is the bias during decoding.

Let $\mathcal{D} = \{(a_1, n_1), (a_2, n_2), \ldots, (a_N, n_N)\}$ be the input data with N number of training examples. Training of the network, to minimize the error is presented by

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \|\mathcal{y}_i - \hat{y}(\imath_i)\|_2^2 + \sigma\sum_{j=1}^{K} d(\delta\|\hat{\delta}_j) + \frac{\gamma}{2}\left(\|\mathcal{W}\|_{\mathcal{F}}^2 + \|\mathcal{W}'\|_{\mathcal{F}}^2\right) \tag{2}$$

Here in this Eq. (2) d denotes the divergence function during network processing, and it varies between target activation function (δ) and hidden layer function $\hat{\delta}_j$. γ and σ are the scalar-valued hyperparameters which are computed with the help of cross validation.

2.1.2. Adaptive sparse demosaicing

In this section we describe the proposed adaptive sparse demosaicing using multi-column method. In this approach several columns are considered and combined to achieve the sparse model of input image. Optimized weights are determined by computing the feature of input image. To make the process as adaptive, we take feature learning process in account. Features are generated using the activation function of hidden layer. By using these features optimal weights are computed by applying the linear combination of the column output as a weighted average.

2.2. Network training

This section deals with the training phase of the network, and this is categorized into three main categories: (a) Sparse Demosaicing Training, (b) Optimal weight computation and (c) Training the weight prediction module.

Training of sparse demosaicing encoders is carried out as mentioned in previous section. In this phase, encoders are provided input set of images along with the artifact set of images.

2.3. Optimal weight computation

At this stage, sparse demosaicing encoders are trained, and in this process a new construction approach is implemented. According to this approach a training set is constructed from the extracted features of the image at hidden layer.

Feature vector is defined as

$$\mathcal{V} = \{f_1, f_2, \ldots, f_C\} \tag{3}$$

where f is the feature and c is optimal column.

In other words, during the sparse demosaicing, activation functions are combined into column feature vectors and column vectors are combined to achieve the final feature vector $\mathcal{V}$.

During this process, output data is stored in a matrix, denoted by $\mathcal{O}$, $\hat{\mathcal{O}} = [\mathcal{y}_1, \mathcal{y}_2, \ldots, \mathcal{y}_c] \in \mathcal{D}_c^{\mathcal{D}}$. In order to determine the ideal weight of the input image, non-linear optimization is performed as

$$\begin{aligned} &\mathit{minimize}_{\{w_v\}} \frac{1}{2}\|\hat{\mathcal{O}}_s - \mathcal{y}\|^2 \\ &\mathit{subject\ to}\ 0 \leqslant w_v \leqslant 1, \forall_c \\ &1 - \delta \leqslant \sum_{c=1}^{C} w_v \leqslant 1 + \delta \end{aligned} \tag{4}$$

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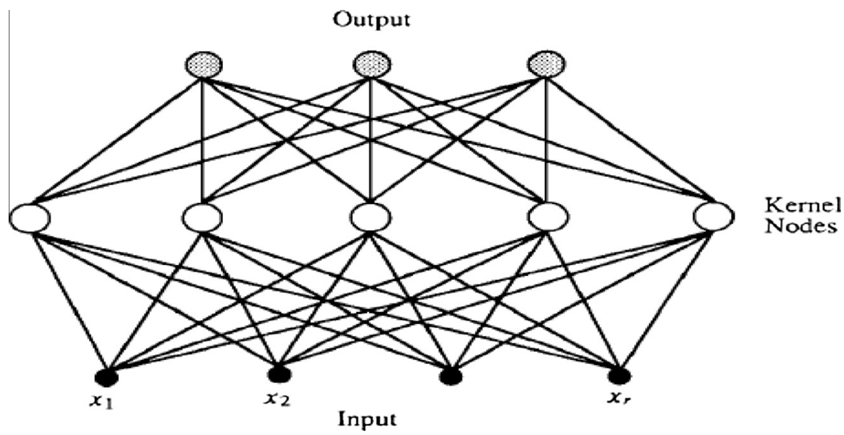

Figure 2 A radial-basis-function network.

Figure 3 Kodak image dataset.

w_v denotes the corresponding weight vector. In order to predict the better weight, overfitting reduction is applied by constraining weight values between 0 and 1.

2.4. Learning and weight prediction

In the final stage of training phase, weights are trained for the prediction module. Input feature vector $\mathcal{V}$ is given to the RBF network for training and a weight ω is produced as output. In the previous section we have discussed the use of weights.

In Fig. 2, RBF classifier is shown in Fig. 2 with one hidden layer. These hidden units have their own centroids and for each input data, distance (d) between input vector and centroid is computed. Output is achieved in the form of nonlinear function of the computed distance; output computed using kernel node depends on radially symmetric function.

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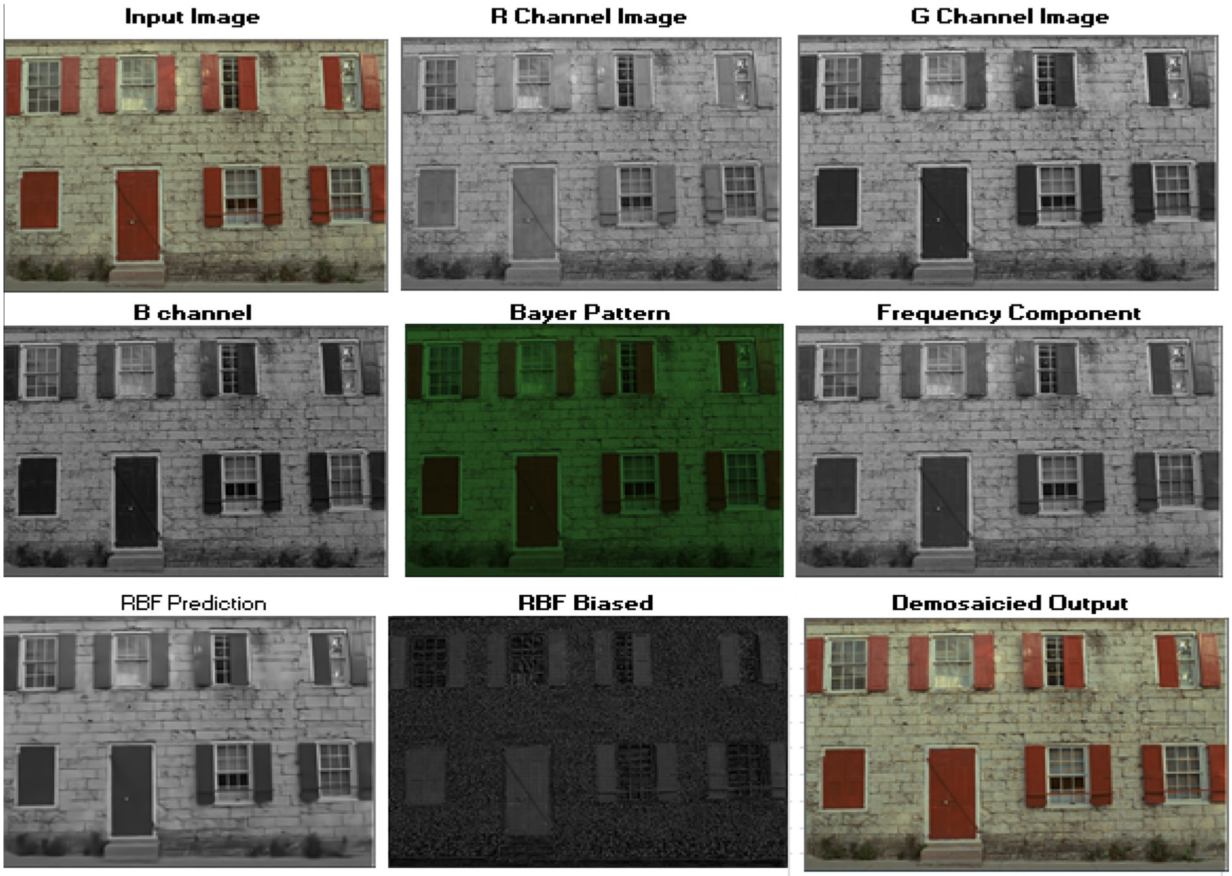

Figure 4 Color image demosaicing using proposed approach.

Table 1 CPSNR performance for Kodak datasets.

Image No.	Red channel	Green channel	Blue channel	CPSNR
1	44.961684	47.126482	44.878127	45.4684
2	47.569826	50.382224	47.933373	48.364426
3	48.7237	50.924423	48.6259	49.230685
4	48.45988	50.758375	48.622206	49.090645
5	45.818929	47.746945	45.808305	46.312345
6	45.540622	48.000812	45.459534	46.097785
7	48.986538	51.063915	48.973676	49.506926
8	44.301506	46.847139	44.267163	44.892057
9	48.611333	50.901377	48.626545	49.180842
10	48.758117	50.988085	48.647905	49.264886
11	46.362693	48.716075	46.459502	46.976475
12(“	48.559634	51.023706	48.3957	49.081713
13	43.90386	45.672082	43.74933	44.307374
14	45.973936	48.401783	46.306826	46.694239
15	47.704291	50.186907	47.89235	48.376657
16	46.900022	49.546575	46.948475	47.541131
17	48.469585	50.25676	48.271657	48.858736
18	45.974683	47.745577	45.742211	46.346174
19	46.787123	49.135867	46.871651	47.395109
20	47.967966	50.161416	48.060492	48.552152
21	46.221668	48.332897	46.110915	46.707524
22	47.013486	49.073725	46.83085	47.459883
23	49.983685	52.405264	50.307359	50.699337
24	45.985386	47.755168	45.233919	46.125203

Table 2 Comparative analysis of proposed work with existing methods.

Image	DL [17]	LDI-NAT [20]	MDWI-N [21]	MDWI [21]	MLRI [22]	MDWI-GF [23]	Proposed
1	26.98	29.08	29.15	29.29	28.97	29.21	45.4684
2	31.28	33.85	34.18	34.33	34.01	34.21	48.36443
3	33.83	37.95	37.81	38.06	38.26	38.69	49.23069
4	34.41	37.2	36.46	37.12	36.45	36.45	49.09065
5	36.34	38.67	38.35	38.59	38.63	38.71	46.31235
6	38.8	40.7	40.82	40.94	40.51	40.57	46.09779
7	37.24	38.65	38.54	38.66	38.76	38.93	49.50693
8	37.27	38.96	39.12	39.23	38.91	38.97	44.89206
9	30.45	33.97	34.36	34.32	35.08	35.15	49.18084
10	29.31	32.78	33.26	33.41	32.58	33.03	49.26489
11	40.92	39.71	37.22	37.94	40.74	39.15	46.97648
12	41.1	39.81	38.12	38.79	41.44	39.58	49.08171
13	39.88	38.43	36.98	37.62	39.31	37.75	44.30737
14	43.31	42.08	40.94	41.6	43.73	41.79	46.69424
Avg	35.79	37.28	36.83	37.14	37.67	37.3	47.46

Table 3 Comparative study of proposed approach.

Methodology used	R channel PSNR	G channel PSNR	B channel PSNR	CPSNR
Gradient based threshold CFA [25]	39.48	43.12	39.85	40.43
RI [26]	37.9	40.95	37.79	38.58
LSSC [27]	40.53	44.31	40.65	41.44
IRI [24]	38.82	42.38	39.15	39.77
Proposed	46.89	49.18	46.91	47.46

Output can be written as

$$\sum_{i=1}^{\mathcal{M}} \mathcal{W}_i \mathcal{K}\left(\frac{\imath - z_i}{\alpha_i}\right) = \sum_{i=}^{\mathcal{M}} \mathcal{W}_i g\left(\frac{\|\imath - z_i\|}{\alpha_i}\right) \tag{5}$$

A number of kernel nodes in the hidden layers are denoted as $\mathcal{M} \in \mathcal{N}$, weight vector is denoted as $\mathcal{W}$, input vector is $\imath$, radial kernel function (symmetric) is $\mathcal{K}$, centroid is z and α_i denotes smoothing function.

3. Results and discussion

This section of manuscript deals with results achieved by applying proposed approach for color image demosaicing. This strategy is implemented using MATLAB tool on publicly available dataset. For performance evaluation, KODAK dataset [19] is considered which contains 24 images in bmp image file format with size of 768×512. According to proposed approach each image is downsampled using Bayer pattern followed by sparse based RBF demosaicing. Proposed scheme is compared with other state-of-art technologies. For the given dataset images objective quality performance is computed in terms of PSNR of red, green and blue channels.

3.1. Performance evaluation

In order to evaluate the performance of the proposed demosaicing scheme, difference of original image and output demosaiced image is computed and measured in image fidelity matrices color peak signal to noise ratio (CPSNR). This measurement is carried out for each channel separately of the image and combined channel performance in average is also measured.

For combined PSNR measurement, color peak signal to noise ratio (CPSNR) is used which is given as

$$CPSNR = 10\log\frac{(255^2)}{\frac{1}{3HW}\sum_i^H\sum_j^W \|I_{orig}(i,j) - I_{demos}(i,j)\|_2^2} \tag{6}$$

where H is height of image, W denotes width, I_{orig} is original input image, and I_{demos} is demosaiced image (see Fig. 3).

By applying proposed approach we show the experimental results for image "1 Stone building" which includes various intermediate results. This analysis is depicted in Fig. 4.

CPSR results for each channel of image are given in Table 1.

Proposed scheme is compared with other state-of-art schemes such as DLMMSE [17], LDI-NAT [20], MDWI [21], MLRI [22] and MDWI-GF [23]. Comparative study is given in Table 2. Here for comparison we have considered 14 images from Kodak dataset. In order to evaluate the performance we have computed CPSNR and compared with the existing methods.

In another comparative study proposed approach is compared with [24–27]. Comparative study of the proposed scheme with other schemes is presented in Table 3.

Table 3 shows the average PSNR and CPSNR performance of proposed system and is compared with other existing techniques. Comparative study shows that the proposed work shows 15.80% improvement in PSNR of R channel, 12.32% improvement in G channel PSNR, 15.05% improvement in

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B channel PSNR and 14.81% improvement in CPSNR when compared to gradient based demosaicing.

Comparing with RI [26] proposed work shows 19.17%, 16.73%, 19.44% and 18.7% improvements in R, G, B channels and CPSNR respectively. Improved efficiencies of proposed work achieved are 13.56%, 9.90%, 13.34% and 12.68% for R, G, B channels and CPSNR when compared with LSSC [27]. Similarly improved performance is achieved as 17.21%, 13.82%, 16.54% and 16.20% for R, G, B channels and CPSNR respectively when compared with IRI [24].

From the comparative study it can be analyzed that the proposed work outperforms when compared with other algorithms for color image demosaicing.

4. Conclusion

In this work, color image demosaicing is studied and based on the challenges faced during other researches, we have proposed a new technique of image demosaicing using sparse based RBF network. According to this process, downsampling is applied on the input image before processing for demosaicing. With the help of this, image sparse model is designed by computing the weights of the given image. The weight components are used to minimize the error during reconstruction. To improve the performance, adaptive demosaicing is used by computing optimal weights for a given image. These optimal weights are used for network learning and prediction of missing color component. Novelty of this work is to adopt the sparse based RBF network and optimal weight computation. Experimental study shows that the proposed approach shows more efficient and robust results when compared to other state-of-art techniques.

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