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Adaptive Image Demosaicing Algorithm Based On K-Nearest Neighbor for Improved Visual Quality

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ABSTRACT

Demosaicing extracts a high quality, full-color image from the incomplete data samples obtained through image sensors via bayer pattern. Healthcare, image forensics, low light photos, etc. use this technique. For a major consideration, this work provides an adaptive demosaicing approach that uses gradient corrected linear interpolation along with k-Nearest Neighbor algorithm to learn from the labelled training set, with the output based on a distance measurement. Signal to Noise Ratio, Peak Signal to Noise Ratio were determined in order to justify the effort and the findings showed that the mentioned method produced better results.

Keywords: Bayer pattern, Demosaicing, kNN, PSNR, SSIM.

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INTRODUCTION

Levery person in his daily life has come across images on his smartphone or iPad. Digital images have worthier than analog images. Digital images have higher resolution and are more suitable for processing computers and smartphones. Digital images play a vital role in medical technology, sensor networks, and even intelligent transportation. Every digital camera has an RGB color image and has different pixel components. The demosaicing algorithm estimates the missing features in the pixel in every color plane. This article proposes a demosaicing algorithm which estimates the missing pixels by interpolating them with fewer color artifacts. Filter bank methods can reduce the aliasing effect problem by applying filter bank methods to the two-dimensional interpolation.

The Bayer pattern filters are still using in digital cameras. Even the Mastcam imaging system used by the Mars rover designed by NASA is to capture the images on the planet mars are used by the Bayer pattern filters. [4] Another algorithm works in iterative mode finds the color difference in image domains and has spatial adaptation criteria for compressing color misregistration. Further, adaptive demosaicing algorithm where the missing green samples are estimated first based on color variance difference with different edge directions and later on the red and blue color components are calculated depending on interpolated green plane and have resulted in best average demosaicing performance subjectively. [5] The different manufactures of camera models have different color demosaicing strategies.

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An article proposed an identified strategy that re-processes the analyzed image with eigen algorithms and builds a set of identifying features for the algorithm. ^[6]

The demosaicing algorithms have the most efficient and quality results for color image acquisition, especially in noisy images. Researchers' challenges in the demosaicing algorithm are false-color artifacts, edge blur in images, and zippering. To overcome such challenges, an architecture to overcome the image restoration problems using two operations jointly, the first one being denoising, and the other is demosaicing on the camera sensors and when assessed on the Microsoft demosaicing dataset relating to Peak Signal to Noise Ratio (PSNR) has resulted in 2.6 dB improvement over conventional state art algorithms.^[7] In other article, the spatial adaption technique with a jacobian matrix with color maps is presented, and it requires only arithmetic operations such as additions, subtractions, and circular shifts.^[8]

The demosaicing with color filter array will help restore the full-color image, exploit the spatial image values, and

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image spectral correlation values and even characterize the demosaicing artifacts with the correlation technique. ^[9] In this article, a new adaptive demosaicing algorithm for images using the kNN is introduced to remove the image's unwanted artifacts.

This paper is classified into four sections. Section 1 explains the literature survey of the demosaicing algorithms and related works. Section 2 describes the proposed system model, i.e kNN. Section 3 discusses the results obtained and the comparison of ten output images with original images and finally the paper is concluded in section 4.

MATERIAL AND METHODS

To tackle classification and regression problems, the K-nearest neighbours approach is employed a lot of the time. Supervised and unsupervised machine learning algorithms

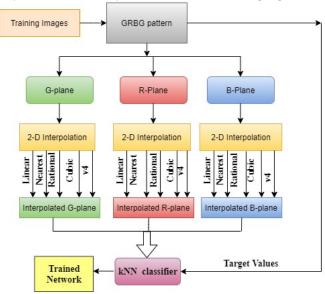


Figure 1: Training procedure for images using KNN-Classifier with neighbour 5



Figure 2: Ten Test images from Kodak Dataset^[13]

exist, with supervised algorithms learning from labelled input data and unsupervised algorithms learning from unlabelled input data. The kNN method will assist create the trained network. A value of k indicates that Nearest Neighbour will use five interpolated result pixel values to compare the original image's RGB values. To begin the training process, a training image is given to the Bayer or GRBG pattern. R, G and B matrixes will be divided by this pattern.

Interpolation is done in two dimensions utilising gradients and five techniques: linear, closest, rational and cubic in each plane (i.e. R plane, G-plane and B-plane). A 7x7 window or kernel size has been selected as the window size. For this arrangement, the proposed technique was evaluated with a variety of window sizes. The training images are given to the Bayer pattern GRBG, [15] which arranges the RGB colour components. Each sensor in the digital camera records RGB data using a Bayer colour filter array. According to the kNN algorithm, pixel values or nearest neighbours should be in close proximity to each other. [16] The demosaic function turns the 2D encoded image into an actual colour image using the interpolation approach. Figure 1 shows how the target values are passed to kNN, which then creates a trained network by employing five nearest neighbours. Once the network was trained, the ten testing images from the Kodat dataset^[13] were loaded and the evaluation metrics for them were measured, as well as the predicted images.

Figure 2 depicts ten original images, including a red door, hats, a portrait of a girl in red, shuttered windows, white water rafters, a girl with a painted face, a farm and pond, two macaws, and a mountain cabin.

RESULTS AND DISCUSSIONS

SSIM and MSSIM

Image quality metric values are shown in Tables 1 and Table 2. Each plane's PSNR, SNR, SSIM, and MSSIM parameters are measured. Five different 2-D interpolation methods are used to reduce the aliasing effect. The training procedure for

Table 1: PSNR for RGB planes

Table 111 State of the planes									
Image No.	PSNR(R)	PSNR(G)	PSNR(B)						
1	37.51	37.4	44.5						
2	42.51	41.43	45.25						
3	45.94	43.19	45.7						
4	38.55	40.12	45.38						
5	46.92	40.1	46.12						
6	35.76	36.71	45.6						
7	43.41	43.8	44.67						
8	35.79	36.48	46.56						
9	43.72	41.19	48.2						
10	43.22	44.49	49.63						
Average	41.33	40.49	46.16						



the kNN was performed on high-quality resolution images for every plane. The image quality metrics SNR, PSNR are mathematical measures of any image quality based on the different resolution images' pixel difference. [14]

$$MSE = \frac{1}{N*M} \sum_{M=0}^{M-1} \sum_{n=0}^{N-1} e(m,n)^{2}$$
 (1)

$$PSNR = 10 \log \frac{s^2}{MSE} \tag{2}$$

Similarly, the SNR is also a measure that estimates the quality of the reconstructed image with respect to the original image. The Formulas for evaluation are given by equation (1-9). Where s=65535, for the 16-bit image.

$$\mu_x = \frac{1}{T} \sum_{i=1}^{T} x_i \tag{3}$$

$$\mu_{y} = \frac{1}{T} \sum_{i=1}^{T} y_{i} \tag{4}$$

Table 2: Evaluation Metrics using kNN

lmage No.	SNR	SSIM	MSSIM						
1	78.5	0.9983	0.9995						
2	81.04	0.9988	0.9943						
3	91.14	0.9981	0.9981						
4	81.76	0.9974	0.9983						
5	82.42	0.9987	0.9991						
6	81.14	0.9967	0.994						
7	92.73	0.9975	0.9985						
8	79.35	0.9964	0.9991						
9	91.49	0.9966	0.9976						
10	95.85	0.9977	0.9989						
Average	85.54	0.9976	0.9977						

Table 3: Comparison of PSNR Values

lmage	Bi-						Proposed kNN
No.	Linear	[8]	[9]	[10]	[11]	[12]	method
1	37.12	38.3	39.1	39.6	39.9	40.1	38.81
2	34.5	40.5	41.5	41.7	42.8	42.5	42.79
3	33.77	38.6	40	40.6	40.6	40.6	44.76
4	33.5	40.8	41.6	42.1	42.6	40.8	40.53
5	29.28	35.3	25.7	36	36.7	35.5	43.24
6	32.35	37.3	39	39.4	39.4	39.9	37.73
7	31.64	38.5	40.7	40.4	41.4	39.5	43.93
8	30.47	36.5	37.8	38.2	38.5	36.6	37.69
9	35.21	41.5	41.9	42.2	42.9	42.5	43.51
10	26.71	31.9	34.7	35.4	34.8	34.3	45.04
Average	32.45	37.9	38.2	39.5	39.9	39.2	41.8

$$\sigma_{x}^{2} = \frac{1}{T - 1} \sum_{i=1}^{T} (x_{i} - \bar{x})^{2}$$
(5)

$$\sigma_y^2 = \frac{1}{T-1} \sum_{i=1}^{T} (y_i - \bar{y})^2$$
(6)

$$\sigma_{xy}^{2} = \frac{1}{T - 1} \sum_{i=1}^{T} (x_i - \bar{x})(y_i - \bar{y})$$
(7)

$$SSIM(x,y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$
(8)

$$MSSIM = \frac{1}{P} \sum_{j=1}^{P} .SSIM_j$$
(9)

Image 10 has the highest SNR, and this translates to an overall improvement in visual quality. There are 10 separate test photos with varied resolutions, and the SSIM and MSSIM values are calculated for each of them. SSIM values for picture 6 are the lowest, while MSSIM values for image 8 are the highest. It is 0.9986 for SSIM and 0.9984 for MSSIM. As a result of this, the image quality is improved.

Data from state-of-the-art procedures are shown in Table 3. Image quality can be improved by using the kNN algorithm. According to the sources, [8-12] the PSNR values for ten Kodak pictures suite were calculated. Ten photos' PSNR values are averaged. There is a 22.3 percent improvement in efficiency using the bilinear method compared to the kNN method, which has an average PSNR value of 32,45. Comparing other researches, [8,9] the overall efficiency is up 17.8 percent, and 17.2 percent when compared to [8]. This approach has a PSNR average of 39.54. This PSNR score was compared to KNN and showed a 16.43 percent improvement. When the new colour filter array interpolation architecture method is used to the Kodak image suite 10 pictures, the

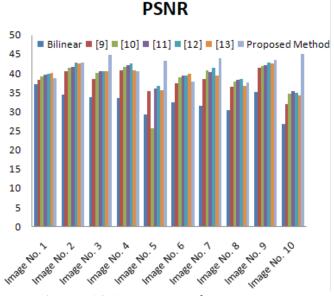


Figure 3: PSNR comparisons for Images1 to 10





(a) Red door



(c) Shuttered Windows



(b) Hats



(d) portrait of girl in red

Figure 4: Output Images

average PSNR value is 39.25, resulting in an improvement of 18.2%. Finally, image demosaicing with content and colour correlation has a PSNR of 39.25.

Corresponding to all conventional methods such as bilinear method, principal vector method, spectral and spatial method, colour filter array interpolation method, and image demosaicing process with content and colour correlation techniques, the proposed method has shown improvement in picture quality, resolution size, and predicting pixel colour values, as shown graphically in Figure 3.

The ten Kodak photos were first chosen, and then converted to GBRG patterns using MATLAB code. The picture metrics are computed by simulating the kNN demosaiced image in MATLAB. The picture metrics were evaluated using the image processing toolbox in MATLAB and native routines. Figure 4 depicts the comparison of four test photographs with kNN demosaiced images, as well as the calculation of image metric quality values.

Conclusion

Using training approaches, this adaptive demosaicing method generates high-quality photos. This technique is completely reliant on the machine learning training process. The five two-dimensional interpolation approaches are applied to the GBRG photos in order to evaluate the missing pixels in the Kodak image suite. This suggested technique outperforms numerous state-of-the-art methods by generating reconstructed RGB plane images utilising five different types of two-dimensional interpolation methods. Image quality metrics are used to evaluate the trained images. The MATLAB tool is used to create PSNR, SNR, SSIM, and MSSIM values from ten original photos, including a red door, hats, a portrait of a girl in red, shuttered windows, white water rafters, a female with a painted face, a barn and pond, two macaws, and a mountain cabin. For all test photos,

the kNN resulted in improved efficiency for the bilinear interpolation method, principal vector method, colour filter array interpolation method, demosaicing method with content, and colour correlation method.

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