

DE-Mosaicing using Matrix Factorization Iterative Tunable Method

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Abstract-A color image is captured through the single image sensor and it is named as the mosaicked image and this is obtained through the CFA where the pixels are arranged such that any one of the color from the given color component is recorded at every pixel. De-mosaicing is absolute reverse of mosaicking, where the process is to reconstruct the full color image from the given incomplete color samples. In past several methods of de-mosaicing have been proposed however, they have many shortcomings such as computational complexity and high computational load, not matching the original images. Hence we have proposed a methodology named as MFIT i.e. Matrix factorization Iterative Tunable approach, the main aim of this methodology is to improve the reconstruction quality. In order to achieve the better reconstruction quality we have used the MFIT algorithm at each iteration this helps in avoiding the image artifacts and it is achieved through the image block adjustment also it reduces the computational load. Moreover in order to evaluate the proposed algorithm we have compared it with nearly 12 algorithms based on the value of PSNR and SSIM, the theoretical results and comparative analysis shows that our algorithm excels compared to the other existing method of de-mosaicing.

Keyword: De-mosaicing, MFIT, Matrix Factorization, Iterative Tunable.

I. INTRODUCTION

Nowadays most people share their picture of various events with people through the internet easily, the demand of DSLR has become widely popular and it has become one of the indispensable device in work as well as life. Moreover, in this entire scenario, the image resolution is one of the eminent aspect for the standard quality of image[1]. Almost all the Digital Camera have been designed through the single color CMOS, which is masked with the CFA(Color filter array), the CFA are used for capturing the single color at every pixel [2]. De-mosaicing is defined as the process of color image reconstruction through the estimation of missing samples of color; mosaic is the word which is used reconstruction of the original scene in its true color[3]. De-mosaicing is also known as the CFA interpolation, so in other words it refers to the reconstruction problem of the image from the samples of CCD(Charge Coupled Device)[4], the reconstruction takes place based on the three color image without the complete information of image. In other words using the de-mosaicing method, the detail color information can be maintained.

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Typically the CFA constitutes the color sensor at every position of the pixel, hence the color information are measured at every image pixel, for instance if we want to capture the color image it is eminent to either capture the other two color or reconstruct through the data. One of the widely available CFA pattern is named as Bayer CFA[5], it uses the three distinctive primary colors as the filter sensors in order to obtain and reconstruct the RGB data of given scene. In case of low cost production, the digital color camera uses the single chip of CCD; this is done since the single kind of color data can be acquired through each pixel. Moreover in order to re-construct the high visual quality as well as high-resolution images, the CFA has to be placed between the sensor and the lens, later the high quality images are reconstructed. Moreover, it has been noticed that the production cost is much more complicated and high, hence deployment is avoidable. Moreover, if single piece of the CSA is used then it can achieve only insertion and the information collected is not complete hence the image might appearance.

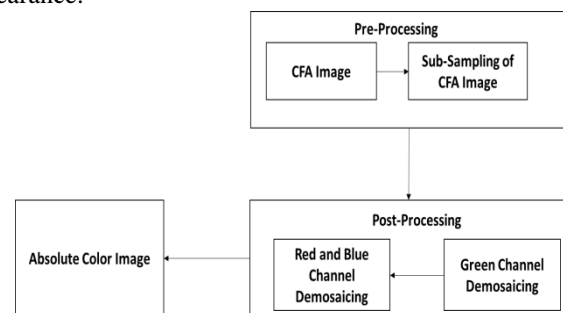


Figure 1 De-mosaicing Process

The above diagram shows the typical de-mosaicing process, it has three different blocks, first block presents the pre-processing, this block shows the Initial stage for the data processing, In here the images are sub-sampled into three distinctive channels and it follows the random pattern which contains the three primary color i.e. RGB. Second block contains the Post-processing, through this block the demosaicing initiates with the green color since it is the largely available color in the CFA and it is made as the guide channel also it is first channel, this in terms results in the absolute image as the output.

The main aim of de-mosaicing is interpolating the missing green, red and blue pixels from the given color this is achieved so that the reconstructed image is as close as to the original image. Moreover, the CC(Computational Complexity) of de-mosaicing is required to be on the lower side for being the cost effective. However, there are many constraints as similar as any other image processing i.e. modelling of the correlation among these three colors, these colors play important role in de-mosaicing.

These colors share almost same characteristics such as edge location and texture, ignorance of such dependency causes the annoying artifacts ,these artifacts are mainly due to the mis registration. Moreover in past several technique has been proposed which has been discussed in the literature survey section. Mainly these methods were proposed to achieve the higher quality image through the exploitation of interplanecorrelation;moreover, the primal issue is finding the best tradeoff between the computational cost and quality of image. These methods were parted into two distinctive categories i.e. iterative[6] and non-iterative[7]. Non-iterative technique is based on the edge directed interpolation for improvising the performance of construction, here the exploitation takes place through the estimation of local covariance information[8] and local gradients[9] and it is based on either difference rule[10] or ratio rule of color[11]. Moreover in [12] ration rule of color were enforced through iterative updating the three color channels, similarly in POCs technique were used for refining the blue and red plane though enforcing the dual convex set constraints and it is observed that iterative approach are more capable of achieving the high quality image.

Hence, in this paper we have proposed a methodology based on the matrix factorization, the main advantage of matrix factorization approach is that it acquires the comparatively less computational load and requires the less memory than the other methodology of image reconstruction. Moreover, Matrix Factorization also has few drawbacks due to the particular type of defining image block set, like otherde-mosaicing reconstruction method Matrix factorization can be implemented using the stride or non-stride image blocks. Striding image block can reduce the block artifacts but has the shortcomings as it comes with high computational cost; the computational cost is more due to the huge number of image blocks involved.Moreover, partition made up of non-striding image block has the lower computational cost, but this causes the block artifacts.Hence, in both cases the three are limitation and cannot be applicable for real life application. Hence, in this paper,the iterative tunable approach has been introduced and methodology is named as MFIT (Matrix Factorization), this particular research work has following contribution:

With the help of matrix factorization we introduce a methodology named as MFIT i.e. Matrix Factorization with iterative tunable approach.

It reduces the computational cost upto the large extend.

It promotes the non-striding image block partition, as it requires the low value singular matrix.

In this at each iteration, MFIT is applied for solving the optimization issue.

One of the main advantage of MFIT is that it suppresses the block artifacts and at the same time it reduces the computation load and these two are achieved through the iterative tunable approach.

This helps in reconstruction of image with the high quality with less computational cost

Our research work is organized in such a way that first section starts with the theoretical definition of de-mosaicing and basic of it ,in the same section later part shows the different virtue related to it, first section ends by briefing the contribution of this research work. Second section describes

the various existng work and their survey, this in terms helps in designing the methodology. Third section shows the proposed methodology along with the flow chart and mathematical notation. Fourth section presents the evaluation of algorithm along with the comparative analysis.

II. LITERATURE SURVEY

In past several de-mosaicing algorithm has been presented some of them are discussed in this particular section, here brief survey of several existing system has been presented and it has been helpful in designing the proposed methodology at first The process in [12] suggested an universal de-mosaicing technique which reconstructs images from various types of CFAs(Color Filter Arrays) for allowing the comparison of the quality of image. This technique calculates the chrominance components through two mechanism(edge-sensing and distance-related weighting to estimate the confidence stages of the inter-pixel chrominancemechanism, and pseudo-inverse-based approximation from the mechanism in a window) and there is reconstruction of the colors through linear transformation, that joins the real Color Filter Arrays(CFA) color component.There are two approximation of the chrominance components. A collection of de-mosaicking algorithm,e.g.[13,14] predicts that the ratio of color of an article that is uniformly colored is constant w.r.t(with respect to) the condition of lighting inside that the article is captured. These type of algorithm first include the G channel (e.g in terms of an edge-directed interpolation and bilinear interpolation), after that there is estimation of B and R channels on consider the B-to-G ratio and R-to-G ratio. Laplacian filter is utilized in [15] to include the missing channel vertically or horizontally, selecting a direction to reserve edges. In [16] authorssuggested an developed method dependent on high-order interpolation, utilizing the Sobel operator to measure the gradients and to detect edges. Some de-mosaicing methods exploit ANN (artificial neural network),e.g.[17]whereas the training pictures learnt offline that are utilized to rebuild misused color of initial pictures. The paper [18] shows the termed sparse based radial base function network for the image of color de-mosaicing: it presents a sparse model of the input image and measure the reconstruction of the error. Sparse de-mosaicing encoders is utilized to pre-train the coatings of a depth of a neural network, in order to decrease the complexity of system complexity inexcursing a network a from mark.

To develop the performance, utilization of adaptivede-mosaicing and calculation of optimized weights in accordance to the few features of the image in order to assume the color component which are lost. The technique in [19] goals at achieving higher quality image but through lower computational time. It is dependent on a regression of a directional difference that studied the prior's offline through training data. The process is a post-processing step, whichcan be joined through other de-mosaicing methods. In individual, it studied offline linear regressors for the continuation among ground truth and demosaiced training image. After that, at runtime, it relates them to the result of the de-mosaicing process.

The multi-level gradient method shows in[20] improves and extends the algorithm [21]: then a first de-mosaicing phase, the multi-level gradient methods corrects the wrong interpolations, consideration of chrominance connection among the channels. A polynomial interpolation-based demosaicing procedure that is suggested in [22]. There are three steps that consist of this method: (i) generation of the predication error on the base of on the PI (polynomial interpolation), (ii) classification of edge that is dependent on the differences of color (ii) to improve the quality of the reducing image the artifacts.

In[23] a process dependent on an advanced NML (non-local mean) filter is presented. The NML filter reflects similar patches, other than similar pixel, to rebuild missed color pixels. A 3-dimensional distance locality that is described to favor the choice of pixels through a structure Same to that of the lost pixels in the area. Some process work under the frequency domain. For example, the efforts clearly suggested an adaptive filtering process to reserve high-frequency details, and consequently stores a higher image quality. Wavelets are utilized in to approximate edge directions, and in [24] to develop the performance of color filter arrays (CFA). In particular, in here the three-step process are implemented by authors (i) Comparison of edge in sub-bands, (ii) transformation of wavelets to extract horizontal and vertical edge information and (ii) downsampling the channels of color. The work in [25] shows a minimization method that joins spatial and spectral representation of original image to resolve the inverse problem of improving samples of missing color from the data of CFA. The representation of spectral sparse defines spectral connection and outcomes from formation model of physical image, whereas the representation of spatial sparse is created on a component analysis of adaptive principal and define the image of local spatial structures.

In a brief survey of demosaicing algorithm can be concluded by noting the point that all these methods have several drawbacks such high computational load, computational complexity or the poor reconstruction, hence we have developed a novel de-mosaicing methodology based on the matrix factorization which is discussed in detail in next section.

III. PROPOSED METHODOLOGY

De-mosaicing is considered to be one of the eminent area in the image processing, and reconstruction of images has been widely popular due to high demand and extensive use of social media. Throughout the above section, we have observed that every other technique lacks from one or other issue, hence in this we have designed a novel method for the reconstruction of image. Our method is named as MFIT i.e. Matrix Factorization Iterative Tunable.

Matrix Factorization method

Let us consider an image by $X \times Y$, then the forward model can be represented by the below equation.

$$U_D = U_o P + G_n \quad (1)$$

Where U_D signifies the under sampled data and G_n signifies the Gaussian noise, U_o is the under sample operator where $U_o : D^{XYD} \mapsto D^{ZD}$ and also $G_n \in D^{ZD}$, $Z < XY$, similarly acquisition can be defined as $: XY/D$. In order to form the matrix factorization, the given underlying image is parted into the two image block i.e. stride and non-stride, the image blocks within the Ω is denoted by $|\Omega|$ and each one is described as $r \in \Omega$, $r = \{1, 2, \dots, |\Omega|\}$. In a given set of image blocks, an image is parted into the various ways, this can be done by displacing the partition by various amount of pixels with the every dimensions. Displacement in shifts can be denoted by using $Disc_\Omega$. these image blocks have the dimensions of $x \times y$.

Let us consider $M_r : D^{XYD} \mapsto D^{ZD}$ as the linear operator, which has been, extracted from the given p image data. This data corresponds to the r^{th} image block of segregated Ω , this in terms generates the matrix $M_r(p)$. The inner product $\langle E, F \rangle_{D^{xy \times D}} = recon(tr(E^H F))$ then the M_r^* satisfies the below equation.

$$\langle M_r(P), Q \rangle_{D^{xy \times D}} = \langle X, M_r^*(Q) \rangle_2 \quad (2)$$

$P \in D^{XYD}$ And $Q \in D^{XYD}$, from the above equation the linear operator can be defined as $L_\Omega : D^{DXY} \rightarrow P$, where $X = D^{|\Omega| \times D \times xy}$, the $L_\Omega P$ component is given by below equation.

$$[L_\Omega P]_r = M_r(P) \quad (3)$$

The inner product is given by the below equation where $r = \{1, 2, \dots, |\Omega|\}$ i.e. equation 4 and the norm is given as in equation 5

$$\langle P, Q \rangle_P = \sum_{q=1}^{|\Omega|} Recon(tr(P_r Q_r^G)) \quad (4)$$

Norm is given as where $P_r, Q_r \in D^{xy \times D}$

$$\|P\|_P = (\langle P, P \rangle_P)^{1/2} \quad (5)$$

Another adjoint $L_\Omega^* : P \rightarrow D^{Dxy}$ is said to be the linear operator which satisfies the below equation.

$$\langle L_\Omega P, Q \rangle_P = \langle P, L_\Omega^* Q \rangle_2 \quad (6)$$

For any $Q \in P$ and $P \in D^{Dxy}$, this can be defined by the below equation.

$$L_\Omega^* Q = \sum_{r=1}^{|\Omega|} M_r^* Q_r \quad (7)$$

Since all the partition contains only non-stride image blocks which can cover entire image, then we have the following equation, since this problem is considered as the NP hard problem and the matrix is nonconvex function, rank of given matrix is approximated using the Matrix norm

$P = L_{\Omega}^*(L_{\Omega}P)$	(8)
$Q = L_{\Omega}(L_{\Omega}^*Q)$	

Let there be any matrix Z which belongs to $D^{G_{n1} \times G_{n2}}$ as

$\ \sigma(Z)\ _p = \ Z\ _{S_p}$	(9)
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$\sigma(Z)$ is said to be the singular values of given vector Z, based on primal dual algorithm [28] the image-block based matrix factorization can be defined in terms integrated norm i.e. for any element $P \in p$ is defined as below

$\ P\ _{1,1} = \sum_{r=1}^{ \Omega } \ P_r\ _{S_1}$	(10)
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Similarly the optimization problem can be formulated as in the below equation, λ is said to be the regularized parameter which maintains the trade-off between the constancy of data and matrix factorization. Below equation presents the generalized version to recover the Matrix Factorization image block from the given under-sampled measurement, assuming the segregation Ω of non-striding/

$\hat{P} = \arg \min_{P \in D^{DXY}} \frac{1}{2} \ U_D - U_o P\ _2^2 + \lambda \ L_{\Omega} P\ _{1,1}$	(11)
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In the above equation i.e. equation 11 λ is considered as the regularization parameter which helps in balancing the trade of among data fidelity and matrix factorization image p . the above equation represents formulation for recovering the matrix factorization p assuming that Ω of non striding, covering image blocks.

Optimization through Iterative Tunable

We use the sparsity driven [29] to solve the above equation, this reduces the order of surrogate functions. Iterative tunable process is applied, our algorithm iteratively reduces the

$f(P, P_0) = \frac{\alpha}{2} \ P - S\ _2^2 + \lambda \ PL_{\Omega}\ _{1,1}$	(12)
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Here, $S = P_0 + \frac{1}{\alpha} U_o^H (U_D - U_o P_0)$ and $\alpha \geq \lambda_{max}(U_o^G U_o)$. The implementation of algorithm is done by minimizing the function in the given equation. This can be written as below equation:

$\ P\ _{1,1} = \max_{\psi \in MF_{\infty, \infty}} \langle \psi, P \rangle_p$	(13)
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$MF_{\infty, \infty}$ is matrix factorization

$\tilde{P} = \arg \min_{P \in D^{DXY}} \frac{1}{2} \ P - S\ _2^2 + \frac{\lambda}{\alpha} \max_{\psi \in MF_{\infty, \infty}} \langle P, L_{\Omega}^* \psi \rangle_2$	(14)
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Later our algorithm makes sure that segregated Ω remains constant throughout the iterations and the updation of

segregation is done in each segregation, this minimizes the block artifacts. Moreover, each image block is independent from one another. Moreover further the optimization is done.

$MF_{\infty, \infty} = \{\Psi \in \mathcal{X}: \ \Psi_r\ _{w_{\infty}} \leq 1, \forall r = 1, 2, \dots, \Omega \}$	(14)
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The above definition along with the ad joint operator L_{Ω}^* the minimized version of the above equation can be represented as

$\hat{P} = \arg \min_{P \in D^{DXY}} \frac{1}{2} \ P - S\ _2^2 + \lambda / \alpha \max_{\psi \in MF_{\infty, \infty}} \langle L_{\Omega}^* \psi, P \rangle_2$	(15)
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Through the above equation we observe that the objective function is concave when it comes to Ψ convex when it comes to X, hence this causes the generation of minimax point, at the minmax point the equation tend to attain the common value. Hence the below equation can be written

$\mathcal{L}(\tilde{P}, \tilde{\Psi}) = \max_{\Psi \in MF_{\infty, \infty}} \min_{X \in D^{DXY}} \mathcal{L}(P, \Psi)$	(16)
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The above equation identify the POF (Primal Objective Function) which is depicted in below equation

$\rho(P) = \max_{\Psi \in MF_{\infty, \infty}} \mathcal{L}(P, \Psi)$	(17)
$= \frac{1}{2} \ p - s\ _2^2 + \frac{\lambda}{\alpha} \ L_{\Omega} P\ _{1,1}$	

Similarly DOF(Dual Objective Function) is given as

$W(\Psi) = \min_{P \in D^{DXY}} \mathcal{L}(P, \Psi)$	(18)
$= \frac{1}{2} \left(\ S\ _2^2 - \left\ S - \frac{\lambda}{\alpha} L_{\Omega}^* \psi \right\ _2^2 \right)$	

Min of \tilde{P} can be known by knowing the max of $\tilde{\Psi}$ and this is achieved by considering the below equation.

$\tilde{P} = S - \frac{\lambda}{\alpha} L_{\Omega}^* \psi$	(19)
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From 18, Using the equation 5, 6, 7, 8

$\max_{\Psi \in MF_{\infty, \infty}} W(\Psi) = \min_{\Psi \in MF_{\infty, \infty}} \frac{1}{2} \left\ S - \frac{\lambda}{\alpha} L_{\Omega}^* \psi \right\ _2^2$	(20)
$= \min_{\Psi \in MF_{\infty, \infty}} \left\ \frac{\lambda}{\alpha} L_{\Omega} S - \Psi \right\ _x^2$	

Max of (18) is found through the projection of $\frac{\lambda}{\alpha} L_{\Omega} S$ to the $MF_{\infty, \infty}$, this projection is achieved using the projection of every $\frac{\lambda}{\alpha} L_{\Omega} S$ components onto the given unit norm ball $UNM_{W_{\infty}}$. Moreover the projection through $UNM_{W_{\infty}}$ is given as



$$\begin{aligned}
 Proj_{UNM_{W_\infty}} \left(\frac{\lambda}{\alpha} [L_\Omega S]_r \right) & \\
 = \frac{\lambda}{\alpha} T_r \left(\min \left(\sigma([L_\Omega S]_r), \frac{\lambda}{\alpha} \right) \right) O_r^c & \quad (21) \\
 = \tilde{\Psi}_q &
 \end{aligned}$$

Hence, from 19 and 21 we get equation 22

$$\Rightarrow \tilde{P} = \sum_{q=1}^{|\Omega|} Proj_r^* \left(T_r dg \left(S_{\frac{\lambda}{\alpha}}[\sigma([L_\Omega S]_r)] \right) O_r^c \right) \quad (22)$$

Equation 23 represents the operator which is applied on the singular vector.

$$\begin{aligned}
 S_{\frac{\lambda}{\alpha}}[\sigma([L_\Omega S]_r)] &= (\max(\rho(P) - \beta, 0) \quad (23) \\
 \beta, 0) &
 \end{aligned}$$

Moreover, $\rho(P)$ is minimized through PRM of image block $\times \|L_\Omega P\|_{1,1}$ in the equation 24

$$\tilde{P} = \min_{P \in D^{XYD}} \rho(P) = PRM_{\times \|L_\Omega \cdot\|_{1,1}}(S; 1/\alpha) \quad (24)$$

$$\tilde{P} = \min_{P \in D^{XYD}} \rho(P) = PRM_{\times \|L_\Omega \cdot\|_{1,1}}(S; 1/\alpha) \quad (25)$$

$$N^b - \gamma_b U_o^H (U_o N^b - y) \rightarrow S^b \quad (26)$$

$$P^b = PRM_{\times \|T_\Omega \cdot\|_{1,1}}(S^b; \gamma_t) \quad (27)$$

$$\frac{1 + (1 + 4e_b^2)^{1/2}}{2} \rightarrow e_{b+1} \quad (28)$$

$$x^t + \frac{e_b - 1}{e_{b+1}} (P^b - P^{b-1}) \rightarrow w^{b+1} \quad (29)$$

Moreover eq.22 shows the reconstruction of image, iterations, from eq.25 to 27 shows the Iterative tunable approach iteration to solve the equation 11, and it is achieved using the given fixed partition.

Matrix Factorization based on stride image block

Lets consider the image block of dimension $uX v$ which is used for covering the image matrix UXV , these image block are stride through the SI pixels and these are stride though NSI pixel, hence the whole striding image block which cover the image are given by the below equation, SIB is the Striding Image Block,

$$SIB = \left(\frac{U + u(1-g)}{NSI} \right) \left(\frac{V + v(1-h)}{SI} \right) \quad (30)$$

Lets consider L as the non-striding partition this corresponds to the P striding image block, then the optimized problem is given in the below equation

$$\begin{aligned}
 \tilde{P} = arg \min_{D \in D^{XYD}} & 0.5 \|U_D - U_o P\|_2^2 + \quad (31) \\
 \lambda \cdot gh \sum_{\Omega \in \Gamma} & \|L_\Omega P\|_{1,1}
 \end{aligned}$$

Matrix factorization with iterative tunable approach

Earlier part of the section shows that the fixed partition remain constant throughout the iterations, however in here through the iterative tunable approach updates the partition in every iteration, this causes the reduction in artifacts. The main advantage with iterative tunable approach is that it achieves the time invariant even without stride image block and this helps in less computational consumption.

IV. RESULT AND ANALYSIS

In this section, our methodology is evaluated to prove the efficiency of methodology, in order to prove we have simulated in-house by using the MATLAB as a language and ran it on the windows workstation with i5 processor along with 2 GB NVidia Graphics and packed with 8 GB RAM. In order to evaluate our proposed methodology i.e. MFIT, we have used the two standard color image datasets namely IMAX and Kodak datasets, these two datasets were used for the benchmark comparison. IMAX dataset has 18 images of size 500x 500 pixels and the Kodak dataset consists of 12 image of same size.

Our methodology were compared with 13 different methodology based on the two parameter i.e. PSNR and SSIM. PSNR and SSIM are the two well-known image quality matrices. Moreover, there is no particular rule for selecting the PSNR or SSIM.

PSNR is calculated using the formula and it is computed through taking square peak value in the given image and divided by the MSE (Mean Square Error), it is used for measuring the image quality after the reconstruction process. PSNR is the error metrics, which is used for comparing the compression quality of the image. The below table shows the comparison analysis based on the PSNR, the image is taken from the Kodak Dataset, these comparison takes place with 13 different algorithm. In comparison with the other algorithm, MFIT possesses the PSNR value of 45.13 db. Higher PSNR indicates the better reconstruction. In case of lossy image when the bit depth is 8 bit, typical value of PSNR is between 30 db and 50db.

SSIM

SSIM i.e. Structural Similarity Index is one of the perceptual metric which quantifies the degradation of image quality, these degradation might be caused by the losses in data transmission or the data compression. In here, it is data compression. SSIM evaluates the visual quality along with the local scaling of spatial correlation which consists of three main components i.e. cross-correlation, variance and mean. This is based on the particular premise where HVS (Human Visual System) is evolved for processing the structural information from the natural images,

DE-Mosaicing using Matrix Factorization Iterative Tunable Method

it employs the modified measure of the spatial correlation between the test images and the pixel of reference, this in terms quantifies the image structural degradation. It predicts the subjective along with sophisticated QA algorithm.

Table 1 Comparison of various methods on KODAK Datasets









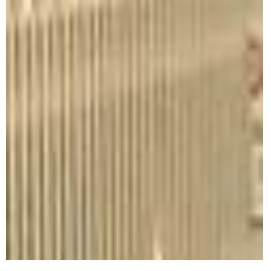
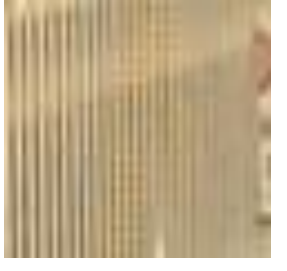
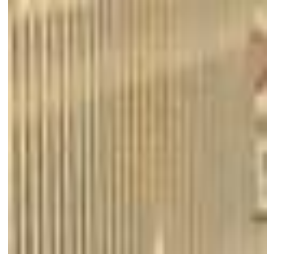
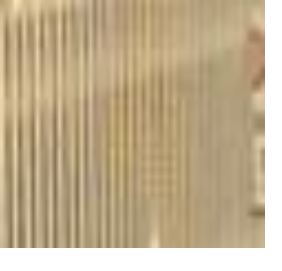




			
(a) Original Image	(b) Origin patch	(c) DLMMSE[26] (39.85dB)	(d) GBTF [27] (40.29dB)
			
(e) LSSC [28] (43.51dB)	(f) NAT [29] (28.67dB)	(g) OSAP [30] (30.85dB)	(h) NN [31] (34.63dB)
			
(i) DJDD [32] (39.63dB)	(j) ARI [33] (35.62dB)	(k) MLRIwei [34] (36.26dB)	(l) FR [35] (36.72dB)
			
(m) JD [36] (42.06dB)	(n) Existing(GCBI)[37] (34.1B)	(o) Existing(GBTF) [37](41.53dB)	(p) Proposed(45.134354)

Table 2 shows the comparative analysis based on PSNR and SSIM with different methodology based on imax dataset, in here we observe that the PSNR value of PSNR is 44.82 and SSIM is 0.9971, this shows that proposed methodology performs better than the other existing technique.

Table 2 comparison analysis of different methodology

Methodology	PSNR(in dB)	SSIM(Co-relation)
DLMMSE [26]	34.466	0.9561
GBTf [27]	34.376	0.9763
LSSC [28]	36.148	0.9854
NAT [29]	36.254	0.9631
OSAP [30]	33.047	0.9652
NN [31]	40.603	0.9925
DJDD [32]	36.927	0.9868
ARI[33]	37.749	0.9905
MLRIwei [34]	36.894	0.9866
FR [35]	37.449	0.9822
JD [36]	36.532	0.9676
Existing (GCB)[37]	37.621	0.9882
Existing (GBTf)[37]	37.293	0.9873
Proposed	44.82	0.9971

KODAK DATASET

Table 3 shows the comparative analysis of different techniques with the Kodak datasets, the below result is generated from the average value of Kodak dataset. The average PSNR value of 24 images are 45.58 db which is better the other state of art technique and existing and average SSIM value of SSIM value is comparatively higher than other technique. The comparative analysis of Kodak dataset indicates that MFIT performs better than the other technique.

Methodology	PSNR	SSIM(Co-relation)
DLMMSE [26]	40.11	0.9858
GBTf [27]	40.623	0.9887
LSSC [28]	41.445	0.9936
NAT [29]	37.714	0.9818
OSAP [30]	39.165	0.99
NN [31]	40.603	0.9925
DJDD [32]	41.45	0.9868
ARI[33]	39.749	0.9937
MLRIwei [34]	39.749	0.9905
FR [35]	39.171	0.99
JD [36]	41.002	0.9923
Existing (GCB)[37]	42.041	0.9941
Existing (GBTf)[37]	42.122	0.9944
proposed	45.58	0.9969

V. CONCLUSION

In this paper we have presented a novel, efficient and fast de-mosaicing methodology named MFIT i.e. Matrix factorization Iterative Tunable approach which provides the similar level of reconstruction when compared to the striding image block based matrix factorization in terms of quality of the image. Moreover, apart from the better

reconstruction when compared to the other similar methodology is that it also reduces the computational load and computational complexity. The MFIT technique suppresses the artifacts with the retention of convergence rate. The experimental analysis and results shows that our algorithm outperforms the different state-of-art technique including the existing system in terms of PSNR.

Although MFIT performs better than the other technique, it is still in infancy way of using matrix factorization technique with iterative approach and still there needs enormous research in order to implement. Moreover, performance can be improved and also it is interesting to see how our algorithm performs with other parameter with the different constraints.

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DE-Mosaicing using Matrix Factorization Iterative Tunable Method

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