Artificial Bee Colony Based Content Adaptive Color Filter Array for Demosaicing

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Abstract—In the recent years, Digital cameras have become more dominant in the image capturing process. For low price digital cameras, concept of Bayer layer is more famous by the name, color filter array (CFA). An approach to produce full color image from the incomplete color sample output of a graphic sensor overlaid with a color filter array is called demosaicing. It can be called color reconstruction or CFA interpolation. Image demosaicing becomes major section of research in vision processing applications. A number of strategies have been developed like bilinear interpolation, constant hue based interpolation, edge adaptive interpolation etc. to produce full color image in demosaicing and the latest one is content adaptive CFA. The content adaptive strategy is simple as compared to the other interpolation strategies, but still there exist some limitations of this technique like static window size, large memory requirements. In this paper, we have proposed an algorithm: Artificial bee colony based content adaptive CFA for demosaicing which further will improve the working of content adaptive CFA. The proposed method has been developed to optimize the window size for each image and to overcome the limitations of the content adaptive strategy. This algorithm provides the best results on the behalf of MSE, PSNR, AD and RMSE parameters as compared to the other strategies.

Keywords—Demosaicing; interpolation; Color filter array; content classification; artificial bee colony; Average Difference.

1. INTRODUCTION

Digital image sensors have become the vital part of digital cameras. They are the light touching 'film' that records the image and enables to give a picture. A digital sensor is, in simple terms, composed of three different layers: **Sensor substrate, A Bayer Filter, microlens.** A Bayer filter has alternating red(R) and green (G) filters for odd rows and for even rows, alternating green (G) and blue (B) filters. The presence of green filters is in double amount as compared to red or blue ones, catering to the human eye's higher sensitivity to green light. Since every pixel of the sensor is behind a color (shade) filter, the result is a section of pixel values, each revealing a raw intensity of one of many three filter colors. Thus, an algorithm must estimate for every pixel along with levels of a number of color components, not a single part. A Bayer filtration mosaic is a color filter array for arranging RGB color filters on a square grid of photo-sensors. Particular layout of color filters has been used in most single-chip digital image sensors used in digital camera models, scanners and camcorders make a color image. The filter pattern is 50% green, 25% blue and 25% red, hence called RGBG, GRGB or RGGB. The raw output of Bayer- filter cameras is known as a Bayer pattern image. Since each filtered pixel record only one of three shades, the info from each pixel cannot fully find color on its own. To get a full-color image, many demosaicing algorithms have been properly used to interpolate a couple of complete red, green, and blue values for each level. Fig. 1 represents the GRBG bayer pattern of color filter array.

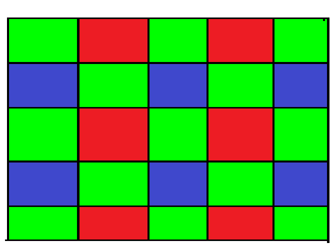


Fig. 1 Bayer Pattern array

Many research works have been proposed in the previous years for demosaicing. Different methods like bilinear interpolation, constant hue based interpolation, gradient based interpolation has been implemented and their comparison based on mean square error has been drawn by R. Ramanath in 2002 [10]. In 2003 R. Ramanath et al. have proposed a flexible demosaicing way in the concept of bilateral filtering. The bilateral selection gives an effective way to adaptively weight a pixel based on its location in the image. This process supplies a mean to denoise, sharpen and demosaicing the image simultaneously [11]. M. Zhao et al**.** have planned a technique for lowering the blocking artifacts in the decoded picture by applying adaptive filtration [12]. L. Shao et al. have planned an integrated resolution up-conversion and retention artifacts elimination algorithm. Regional picture design is classified into object details or code artifacts using the combination of structure information (ADRC) and the activity measure [13]. L. Shao et al. have introduced the classification-based least section trained filters on image quality improvement algorithms. For every algorithm, the working out method is exclusive and separately selected classification methods are proposed [15]. A. Jose et al. have presented the typical concepts of adaptive filtering and its individuals of formulas such as least-mean Square, data-reusing, and recursive least- sections (RLS) [16]. B. Leung et al. represented a luma–chroma demultiplexing algorithm utilizing a least-squares style strategy for the required bandpass filters [17]. L. Shao et al. have proposed a least squares solution that is self adaptive to the visible quality of the input sequence [19]. L. Shao et al. have planned a solution centered on classification and last section qualified filters to repair/patch low-quality video processing modules at the back end of a video chain [18]. L. Shao et al. have proposed a material adaptive demosaicing strategy utilising structure analysis and correlation between the red, green and blue planes [1].

All the above discussed techniques heavily rely on an edge detection mechanism except content adaptive CFA strategy. The content adaptive CFA technique is simple and there is no need of edge detection. The content adaptive strategy finds out least square window size and produces the results by using the filtering mechanism on all the images. There are two phases: offline and online. Offline training mechanism helps to identify the best window size and online phase is runtime phase. This strategy takes too much memory to maintain a lookup table. Look up table maintain the record of the location of the pixels in an image. In this paper, an algorithm named artificial bee colony based content adaptive color filter array has been proposed. The proposed algorithm will further improve the working of content adaptive CFA by optimizing the window size for each image using ABC optimization and produces high quality of the images compared to the content adaptive strategy.

2. METHODOLOGY

In the proposed method, Window size is being optimized by using the artificial bee colony (ABC) algorithm for every image further to improve the working of content adaptive CFA. Content adaptive demosaicing approach finds out the best window size, which is static for all images, by using two stages: training stage and testing stage. During the training phase, all training image patches are being classified by using adaptive range dynamic coding technique to define the texture of the images, and filter coefficient for each class is individually optimized with least square method and stored in a lookup table. Fig. 2 represents the working of the offline training stage:

A. Offline training stage:

Steps of the offline training stage are:

1.) Degrades each input image into the Bayer pattern. Mosaic image in the form of Bayer pattern is available as well as the original plan.
2.) Classification method ADRC is to be used to find the class index for every pixel place.
3.) Least square optimization is conducted to find out the coefficient of the different filters and optimized filter coefficient will be stored in a lookup table for use during demosaicing.

Least square optimization will find out the error between the original image and the filtered image by using the following equation

$$e^2 = \sum_{J=1}^{N_C} (F_{R,c}(J) - F_{F,c}(j))^2 \qquad (1)$$

Where $F_{R,c}(J)$ the reference is image and $F_{F,c}(j)$ is the filtered image.

At the testing stage, the image will be demosaicised, same classification will be performed on the image and according to the class code filter coefficient will be retrieved from the lookup table. Fig. 3 describes the working of testing stage.

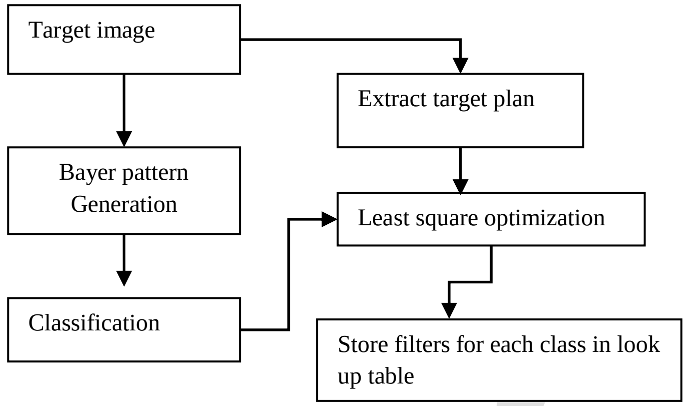


Fig. 2 Offline training procecure [1]

Futhermore strategy has been improved on the proposed method by applying the artificial bee colony optimization.

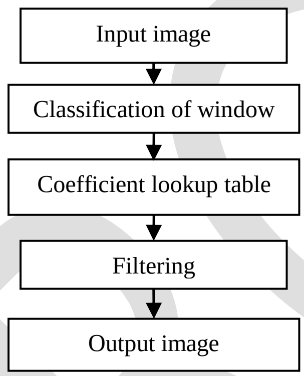


Fig. 3 Online procedure

The artificial bee colony algorithm will optimize the window size to produce better quality of an image. Here the window size is not static nature, its size will be dynamic, i.e. automatic and ABC will find out the optimum window size for every image. Here objective function is:

$$f(x) = \frac{1}{MSE} \tag{2}$$

The aim here is to maximize the objective function $f(x)$ to choose the best window by artificial bee colony. The proposed method will do the work under following methodology:

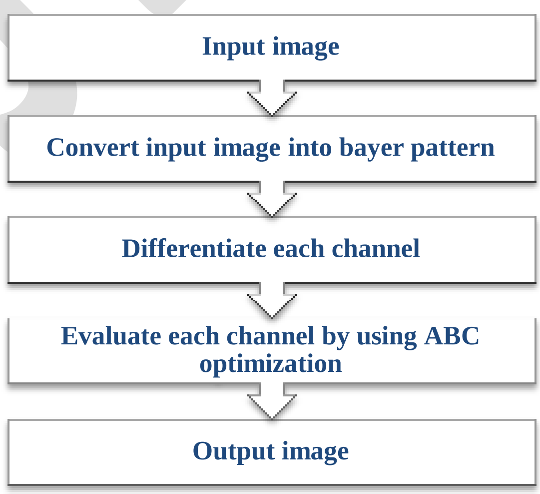


Fig. 4 Methodology

B. Artificial bee colony optimization

Optimization is the act of achieving the perfect result underneath the given circumstances to offer the utmost or the minimum value of an objective function. Two classes of optimization algorithms are: Evolutionary algorithms and Swarm intelligence based algorithms. Most prominent optimization algorithms are: ant colony optimization, particle swarm based optimization and artificial bee colony (ABC) optimization. In the proposed method, artificial bee colony optimization has been utilized because the major advantages which ABC holds over other optimization algorithms include its:

- Simplicity, flexibility and robustness.
- Use of less control parameters.
- Power to handle the objective cost with stochastic nature.
- Simple implementation with standard mathematical and logical operations.

The ABC meta-heuristic has been planned rather recently by Lucic and Teodorovic. It is a bottom-up method which acts partially alike, and partially differently from bee colonies in nature. Artificial bees will be the agents, which covers complicated combinatorial optimization problem. Here every artificial bee computes one means to the problem. There are two phases of the algorithm forward pass and backward pass. Initially in each ahead pass, every artificial bee is examining the search space. From a predefined number of moves it constructs or improves the Solution and also forms a new solution. After obtaining the new partial solution, the bees again go to the nest and move the next phase that is backward pass. In this all artificial bees share information about their solutions. In nature, bees perform a dancing ceremony, and signaled other bees about the quantity of food they have collected and the distance of the area

Figure 4 Methodology

algorithm are:

1.) Intialize population

For every bee do the forward pass

a) Set k=1

b) Evaluate all possible construct moves

c) Acc. To evaluation choose one move using route wheel

d) K=k+1;

If

{

P <= NC

Goto step b

}

2) All bees are back to hive

3.) Sort bees by using objective function

$$\frac{1}{MSE}$$

4.) Every bee decides randomly whether to continue its own exploration and become a recruiter or to become a follower. (High function high change)

5.) For every follower choose a new solution for recruiter by wheel.

6.) If the stopping condition not met go to step 2.

7.) Choose the best solution.

In the proposed method, the working of three phases of the ABC algorithm with the combination of content adaptive CFA is as follows: The very first phase will be **employed bee phase:** population will be intialized (p=1) by randomly selected some pixel as the food sources. Employed bees exploit the food sources and generate the different solutions on the randomly selected food sources by making the iterations (k=1 to n), where n is the maximum number of cycles. The position of food source would be replaced with new one by k+1 to generate new solutions. If the previous existing solution has dominated value than the value of new one, then it will remain same otherwise it will be replaced by the new solution. In order to optimize the best solution image will pass through the second phase i.e. **onlooker bee phase**. Second phase check the probability of all the solutions by using the following equation:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \qquad (3)$$

Where fit_i is the fitness of the solution i which is proportioned to the nectar amount, i.e. in the proposed method, nectar amount will be the interpolated values of the pixels of the position i and SN is the food source that is to say number of pixels which is equal to the number of employed bees or onlooker bees. The third phase is onlooker phase: onlooker phase will find out the new pixels to find out the new solutions on the pixels of the selected image.

In this way these three phases help to optimize the best window size for each image of the selected dataset.

3. EXPERIMENTAL RESULTS

Kodak dataset image has been used for experimental results. Collected Kodak dataset images are shown in Fig. 5. We have totally collected 15 images from the Kodak dataset for experimental use.

Content adaptive strategy further will be improved by using an artificial bee colony algorithm. The artificial bee colony algorithm will find out the best solutions on the pixels of the image and help to optimize the best window size for each Kodak dataset image.

Fig. 6 shows the result images has been used by content adaptive CFA and Adaptive ABC strategies. Firstly, by performing processing operations on the image, the image has been converted into the GRBG pattern of the bayer filter. After that this image will be recovered by using content based CFA and Adaptive ABC optimization techniques.

The results of these images have been evaluated on the basis of PSNR, MSE, RMSE and AD.

Fig. 5 Kodak dataset images used for the experimental results

(A) (B) (C) (D)

Fig. 6 (A) Input image (B) Bayer image (C) Content based CFA image (D) Adptive ABC image

Adaptive ABC optimization result image will be of high quality as compared to the content based CFA based on these limit.

TABLE 1	Performance evaluations of MSE, RMSE, PSNR and AD of different channel R, G, B by using content adaptive CFA and adaptive ABC technique:				
Method	**Colours**	**MSE**	**RMSE**	**PSNR**	**Average Difference**
Content based CFA	**R** **G** **B**	5 5 6	2.23 2.23 2.44	41.14 41.14 40.34	17.521 16.196 18.029
ABC	**R** **G** **B**	**2** **2** **3**	**1.41** **1.73** **1.41**	**45.12** **43.35** **45.12**	**7.3862** **10.666** **8.4075**

TABLE 1 Performance evaluations of MSE, RMSE, PSNR, and AD of R, G, B.

Table 1 represents the MSE, RMSE, PSNR, AD analysis based on different channels R, G, B by applying content based CFA and Adaptive ABC techniques on the image shown in Figure 4. The MSE values of different colors (R, G, B) by using content based CFA are R=5, G=5, B=6 and by using ABC are R=2, G=2, B=3. RMSE values of content based CFA are (R=2.23, G=2.23, B=2.44) and ABC based CFA is (R=1.41, G=1.73, B=1.41). PSNR values of content based CFA are (R=41.14, G=41.14, B=40.34) and ABC based CFA are (R=45.12, G=43.35, B=15.12). AD values of content based CFA are (R=17.521, G=16.196, B=18.029) and ABC based CFA are (R=7.3862, G=10.666, B=8.4075).

TABLE 2	Performance evaluations of MSE, RMSE, PSNR and AD by using content adaptive CFA and adaptive ABC techniques:			
Method	**MSE**	**RMSE**	**PSNR**	**Average Difference**
Content based CFA	81	9	29.04	81.57
ABC	**42**	**6.480**	**31.89**	**42.72**

TABLE 2 Performance evaluations of MSE, RMSE, PSNR, and AD using content adaptive CFA and adaptive ABC techniques.

Table 2 shows that the results of ABC based CFA technique are better than the results of content based CFA.

In the similar way, an experiment has been performed on the dataset images based on the following parameters:

- **PSNR (Peak Signal to Noise Ratio)**

The term peak signal-to-noise ratio (PSNR) is an expression for the ratio between the largest possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. PSNR is evaluated by

$$PSNR = 10 * \log(255 * 255 / MSE) / \log(10) \qquad (4)$$

Where, 255 is the greatest power of the signal.

- **MSE (Mean Square Error)**

In this research $M \times N$ represents the size of the each image. Where M represents the number of rows and N represents the number of columns. The original image is represented by the function $f(i, j)$ at the location i, j and the filtered image, i.e. full color image is represented at location i, j by $\widehat{f}(i, j)$. the mean square error between original image and demosaicised image is evaluated by using the following equation:

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{J=1}^{N} (f(i, j) - \widehat{f}(i, j))^2 \qquad (5)$$

- **RMSE (Root Mean Square Error)**

The RMSE represents the differences between predicted values and observed values of an input image. RMSE is a good measure of accuracy. The RMSE is the root of the mean square error and it is evaluated by using the following equation:

$$RMSE = \sqrt{MSE} \tag{6}$$

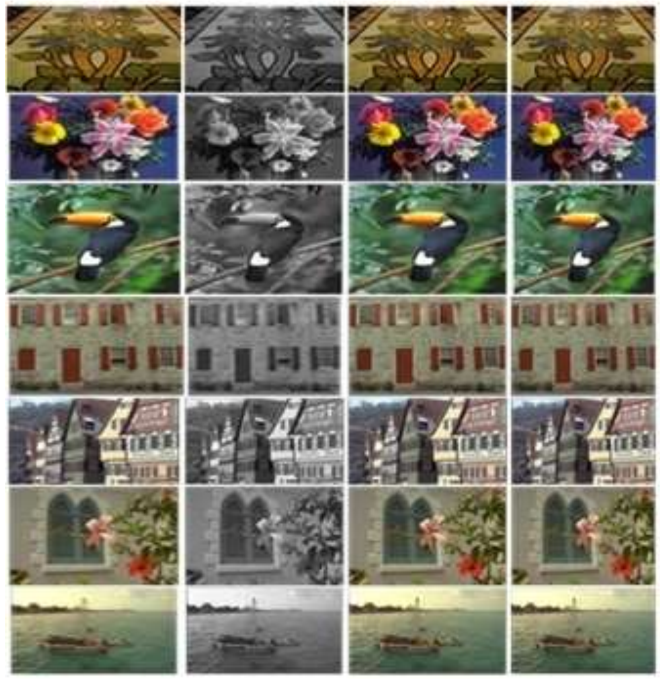
- **AD (Average Difference)**

The average difference represents the mean error between

the original image and the filtered image. AD is evaluated by using the following equation:

$$AD = \frac{\sum_{i=1}^{M} \sum_{i=1}^{N} (f(i,j) - \hat{f}(i,j))}{MN} \tag{7}$$

On the behalf of these limits we have performed the experiment on the selected dataset.Experiment has been conducted in the proposed method on all the selected dataset images are shown in the Fig. 7.



(A) (B) (C) (D)

Fig. 7 (A) Input image (B) Bayer image (C) Content based CFA image (D) Adptive ABC image

In the figure 7, column A represents the input images, column B shows the bayer images, column C and D represents the recovered images by using content adaptive and ABC based CFA techniques.

TABLE 3 Performance evaluations of MSE using content adaptive CFA and adaptive ABC techniques.

TABLE 3	**Performance evaluations of MSE by using content adaptive CFA and adaptive ABC technique**	
Image No.	**Content based CFA**	**ABC Optimization based content based CFA**
	MSE	**MSE**
1	26	9
2	32	14
3	62	18
4	357	142
5	161	49
6	21	9
7	130	39
8	395	141
9	66	23
10	81	42
11	148	45
12	248	78
13	241	10
14	109	36
15	127	42
Average	**146.9**	**46.46**

TABLE 4 Performance evaluations of PSNR using content adaptive CFA and adaptive ABC techniques

TABLE 5	Performance evaluation of RMSE by using content adaptive CFA and ABC optimization based content adaptive CFA

TABLE 4	Performance evaluation of PSNR by using content adaptive CFA and ABC optimization based content adaptive CFA	
Image No.	**Content based CFA**	**ABC Optimization based content based CFA**
	PSNR	**PSNR**
1	33.98	38.58
2	33.07	36.66
3	30.20	35.57
4	22.60	26.60
5	26.06	31.22
6	34.90	38.58
7	26.99	32.22
8	22.16	26.63
9	29.63	34.51
10	29.04	31.89
11	26.42	31.59
12	24.18	29.20
13	34.32	38.13
14	27.75	32.56
15	27.09	31.89
Average	**28.55**	**33.05**

TABLE 5 Performance evaluations of RMSE using content adaptive CFA and adaptive ABC techniques

Image No.	Content based CFA	ABC Optimization based content based CFA
	RMSE	RMSE
1	5.099	3.000
2	5.656	3.741
3	7.874	4.242
4	18.89	11.91
5	12.68	7.000
6	4.580	3.000
7	11.40	6.245
8	19.87	11.87
9	8.120	4.790
10	9.000	6.480
11	12.16	6.708
12	15.74	8.831
13	4.899	3.162
14	10.44	6.000
15	11.26	6.480
Average	**10.51**	**6.230**

In table 3, the performance of both the techniques has been evaluated on the basis of Mean Square Error. The average of content based CFA technique based on MSE analysis is **146.9** and the average of ABC optimization based content based CFA is **46.46**In table 4, the results of all the test images have been evaluated on the basis of PSNR. The average of peak signal to noise ratio of all the images by using ABC optimization based Content based CFA is **33.05** and the average of content based CFA **28.55.**In table 5, the performance of the images has been evaluated on the basis of RMSE. Root Mean Square Error is also a way to evaluate the error between the original image and output image. From the results of both the techniques, it's clear that the result of ABC optimization based technique is better. The average of ABC optimization based content based CFA is **6.230** and the average of content based CFA is **10.51.**

TABLE 6 Performance evaluations of AD using content adaptive CFA and adaptive ABC techniques

TABLE 6	Performance evaluation of AD by using content adaptive CFA and ABC optimization based content adaptive CFA	
Image No.	Content based CFA	ABC Optimization based content based CFA
	AD	AD
1	26.30	9.811
2	32.70	14.19
3	62.10	18.83
4	357.6	142.1
5	161.5	49.55
6	21.21	9.772
7	130.4	39.85
8	395.8	141.1
9	66.59	23.30
10	81.57	42.72
11	148.6	45.24
12	248.9	78.86
13	24.20	10.79
14	109.8	36.19
15	127.0	42.31
Average	**132.9**	**46.97**

In the table 6, the results of the images have been evaluated based on the average difference. Here the average of all the dataset images based on AD by using ABC Optimization is **46.97** and the average of content based CFA is **132.9**. So it's clear that the results of ABC optimization technique are better than the content based CFA.

TABLE 7	**Performance evaluation of MSE, RMSE, PSNR and AD of different R, G, B Channel by using content adaptive cfa and adaptive ABC technique of all the dataset images:**								
		Optimized adaptive ABC				**Content based CFA**			
Image No.	**Colour**	**MSE**	**RMSE**	**PSNR**	**AD**	**MSE**	**RMSE**	**PSNR**	**AD**
1	**R**	5	2.23	41.14	16.00	10	3.16	38.13	32.98
	G	6	2.44	40.34	18.71	10	3.16	38.13	30.42
	B	4	2.00	42.11	12.63	09	3.00	38.58	29.58
2	**R**	7	2.64	39.67	23.35	13	3.60	36.99	41.81
	G	9	3.00	38.58	27.55	13	3.60	36.99	39.64
	B	5	2.23	41.14	17.02	21	3.46	37.33	36.28
3	**R**	07	2.64	39.67	23.01	22	4.69	34.70	67.14
	G	13	3.60	36.99	39.34	24	4.89	34.32	72.51
	B	09	3.00	38.58	29.53	25	5.00	34.15	76.46
4	**R**	58	7.61	30.49	174.0	137	11.7	26.76	411.4
	G	86	9.27	28.78	260.0	131	11.7	26.95	393.5
	B	55	7.41	30.71	165.7	135	11.6	26.82	406.3
5	**R**	6	2.44	40.34	18.83	7	2.64	39.67	21.02
	G	7	2.64	39.67	22.89	11	3.31	37.71	33.69
	B	8	2.82	39.09	24.19	11	3.31	37.71	33.69
6	**R**	21	4.58	34.90	64.42	51	7.14	31.05	154.9
	G	24	4.89	34.32	74.82	46	6.78	31.50	139.5
	B	21	4.58	34.90	64.19	50	7.07	31.14	150.5
7	**R**	55	7.41	30.72	166.91	149	12.2	26.39	447.1
	G	93	9.64	28.44	279.53	144	12.0	26.54	443.4
	B	54	7.34	30.80	162.16	145	12.0	26.51	437.5
8	**R**	24	4.89	34.32	73.53	30	5.47	33.35	91.35
	G	24	4.89	34.32	74.66	33	5.74	33.94	100.8
	B	24	4.89	34.32	74.00	27	5.19	33.81	83.74
9	**R**	2	1.41	45.12	7.386	5	2.23	41.14	17.52
	G	3	1.73	43.35	10.66	5	2.23	41.14	16.19
	B	2	1.41	45.12	8.407	6	2.44	40.34	18.02
10	**R**	22	4.69	34.70	68.40	35	5.91	32.69	105.6
	G	27	5.19	33.81	82.55	35	5.91	32.69	105.6
	B	23	4.79	34.51	70.64	31	5.56	33.21	95.34
11	**R**	19	4.35	35.34	57.96	52	7.21	30.97	157.5
	G	32	5.65	33.07	97.48	56	7.48	30.64	170.9
	B	18	4.24	35.57	55.99	51	7.14	31.05	155.1
12	**R**	34	5.83	32.81	104.11	90	9.48	28.58	272.4
	G	54	7.34	30.80	164.93	94	9.69	28.39	284.3
	B	35	5.91	32.69	106.00	92	9.59	28.49	276.4
13	**R**	4	2.00	42.11	14.08	8	2.82	39.09	26.16
	G	7	2.64	39.67	21.26	10	3.16	36.13	30.65
	B	4	2	42.11	13.68	8	2.82	39.09	26.62
14	**R**	15	3.87	36.36	45.20	39	6.24	32.22	118.7
	G	25	5.00	34.15	77.01	42	6.48	31.89	126.4
	B	15	3.87	36.36	47.13	38	6.16	32.33	114.9
15	**R**	14	3.74	36.66	42.63	40	6.32	32.11	120.1
	G	30	5.47	33.35	92.95	52	7.21	30.97	157.6
	B	14	3.74	36.66	42.35	39	6.24	32.22	119.7
Average	**RGB**	**22.7**	**4.31**	**36.41**	**69.72**	**46.26**	**6.105**	**33.43**	**139.7**

From the above table 7, it is clear that the results of MSE, PSNR, RMSE, and AD of the adaptive ABC technique are better than the content adaptive strategy. In the adaptive ABC technique the average of MSE of all the images is **22.7** and the average of MSE of all the images of the content adaptive CFA is **46.26**. Similarly the average of RMSE, PSNR and AD of the adaptive ABC technique is 4.31, 36.41, 69.72 and the average of these parameters of the content adaptive CFA is 6.105, 33.43 and 139.7. So from the above results, it's clear that the Adaptive ABC technique provides better quality of images as compared to the content adaptive CFA technique.

4. CONCLUSION

The proposed work handles improving the content based color filter array further by using artificial bee colony in order to optimize the window size. These works have centered on reducing the color artifacts and maintain the quality of the images. The overall objective of the dissertation is to create and implement the artificial bee colony and content based color filter array. we have choosen ABC optimization because the major advantages which ABC holds over other optimization algorithms include its: Simplicity, flexibility and robustness, Use of fewer control parameters compared to many other search techniques, Ease of hybridization with other optimization algorithms, Ability to handle the objective cost with stochastic nature, Ease of implementation with basic mathematical and logical operations. The proposed methodology has taken a full color image as an input image and then converts this image into Bayer pattern. There are three channels presented into a bayer converted image and these channels are Red, Green and

Blue. Differentiate each channel and interpolate each channel by using optimized adaptive artificial bee colony algorithm. The comparison has clearly shown that the proposed over the available techniques.

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