A Hybrid Genetic Fuzzy System for Color Filter Array Interpolation

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***Abstract* — As digital cameras become more powerful and smaller, Charge-Coupled Device sensors still associate only one color of a pixel. This color mosaic called Bayer Pattern must be processed to get a high resolution color image. Each interpolated image pixel has a full color spectrum based on surrounding pixel colors. This study proposes a new adaptive Color Filter Array interpolation model. For normal image regions hue technique is used while edge regions use the new technique. It is proposed to apply fuzzy logic and fuzzy rule selection is based on Genetic Algorithm using random local search to enhance the Peak Signal to Noise Ratio.**

***Index Terms*— Charge coupled Devices, Fuzzy logic, Genetic algorithm, Interpolation, PSNR.**

I. Introduction

In single chip digital cameras, color images are got by interpolating a Color Filter Array (CFA). Charge Coupled Device (CCD) arrays in digital cameras do not capture full red, green and blue color planes due to hardware limitations. Instead, they capture a sparsely sampled image of each color plane and interpolation reconstructs original colors. Digital color cameras use a single CCD sensor with a CFA. Blue (B), red (R), and green (G) tri-stimulus value estimates are obtained on three interleaved sampling structures which jointly form a CFA sampling structure.

A high quality edge-adaptive color interpolation approach for Complement CFA was presented by Chen and Wang [1]. Two luminance signal estimates were made at every pixel under different hypotheses on edge directions using bilinear interpolation. Both the sampled signal and the two estimates were used to assist final interpolation. A post-processing step to suppress demosaicking artifacts by adaptive filtering was presented. Experiments confirmed this algorithm's performance objectively and subjectively.

Demosaicking is the first step of image processing of digital still cameras. If noise and blurred edges exist from the onset of image reconstruction, a post-processing can do little to improve the quality of the reconstructed image. A demosaicking method was proposed by Chen and Chang to prevent the occurrence of color artifacts [2]. By detecting the edge characteristics of a digital image, accurate weights can be obtained for image interpolation, before refinement was done in post-processing. After comparing the experimental results with those of previously proposed methods, it is found that the proposed method can effectively reduce color artifacts and enhance image quality. A new framework for image demosaicking based on minimization of a variational function under consistency constraint with available raw data to demosaick images acquired with a completely arbitrary CFA was proposed by Condat [3]. The variational approach was where a reconstructed image has a maximal smoothness under consistency constraint with measurements. This optimization problem is reduced to a large, linear equation sparse system to solve, for which was proposed an iterative algorithm. Though a linear approach, it yielded visually pleasing demosaicked images, providing a robust framework to compare CFAs performances. This formalism is linear, robust, and generic, as the CFA is arbitrary.

A novel demosaicking approach based on existing directional filtering/weighting technique was proposed by Dengwen [4]. The study's contributions are twofold. The advantages and limitations of existing directional filtering/weighting techniques, and improved two techniques to suppress common demosaicking artifacts was first analyzed, then a new scheme for color component reconstruction was presented. Results showed that the new method outperformed recent six state-of-the-art demosaicking methods regarding terms subjective and objective measures.

To acquire color information, a preferred solution places a CFA before a sensor. The array consists of colored transparent material mosaic permitting a portion of the spectrum to pass. A CFA can be denoted by a triplet

$$cfa[n] = [c_r[n], c_g[n], c_b[n]]^T \in [0, 1]^3 \qquad (1)$$

Equation (1) represents relative percentages of the three components R, G, and B information kept at pixel location n. A new and simplified derivation of the frequency-domain representation of color images sampled with the Bayer color filter array was presented by Dubois [5] with excellent results.

A new universal demosaicking method drawn from lessons learned in Bayer demosaicking designs was introduced by Gu, applicable to arbitrary array patterns [6]. Bayer demosaicking's data-dependency was recast as a parsimonious reconstruction of the underlying image signal, inherently sparse in some representation. Using filter banks' properties this principle yielded a nonlinear recovery method consistent with state-of-the-art Bayer demosaicking methods.

A new, self-learning approach to the problem via support vector regression was presented by He [7]. In contrast to prior learning-based demosaicking methods, the new approach extracts an image-dependent information in constructing a learning model, without needing additional training data. Experiments showed that the new method outperformed state-of-the-art techniques in subjective and objective image quality measures.

The Bayer pattern is a widely used CFA configuration where for 50% of pixels, the green component is given, and the remaining pixels are given red or blue components. Bayer pattern, also called CFA or a mosaic pattern, comprises of a repeating array of red, green and blue filter material atop each spatial location in the array shown in figure 1.

R_{11}	G_{12}	R_{13}	G_{14}	R_{15}	G_{16}	R_{17}
G_{21}	B_{22}	G_{23}	B_{24}	G_{25}	B_{26}	G_{27}
R_{31}	G_{32}	R_{33}	G_{34}	R_{35}	G_{36}	R_{37}
G_{41}	B_{42}	G_{43}	B_{44}	G_{45}	B_{46}	G_{47}
R_{51}	G_{52}	R_{53}	G_{54}	R_{55}	G_{56}	R_{57}
G_{61}	B_{62}	G_{63}	B_{64}	G_{65}	B_{66}	G_{67}
R_{71}	G_{72}	R_{73}	G_{74}	R_{75}	G_{76}	R_{77}

Figure 1 Bayer Pattern CFA Interpolation

The problem of color filter array design and its implications for spatial reconstruction quality is by simultaneously maximizing spectral radii of luminance and chrominance channels subject to perfect reconstruction after proving sub-optimality of a wide class of current array patterns [8] was presented by Hirakawa. It ensures a constructive method for its solution yielding robust, new panchromatic designs implementable as subtractive colors. Empirical evaluations of multiple color image test sets support theoretical results indicating the potential of such patterns to increase spatial resolution for fixed sensor sizes, and to improve reconstruction fidelity in addition to reducing hardware complexity.

The simplest color reconstruction is given by a bilinear interpolation, where a pixel's missing color components are found by averaging corresponding given components in a 3 by 3 local window around the pixel.

Image artifacts are due to bilinear interpolation which is abrupt and unnatural hue change. To offset this, in Hue-Based Interpolation, the hue of a color has to be maintained so that there are no sudden jumps in hue except the edges. Equation (2) gives the calculation of red hue value HR and a blue hue value H_B.

$$H_R = R / G,\ H_B = B / G \qquad (2)$$

The green plane is first interpolated after this hue is interpolated. The estimated values G_{33}, G_{35}, G_{53}, G_{55} is taken after the first pass interpolation. For example, equation (3) gives the red plane is estimated and is represented by,

$$R_{4,4} = G_{4,4} \times \left[\frac{\left(\frac{R_{3,3}}{G_{3,3}} + \frac{R_{3,5}}{G_{3,5}} + \frac{R_{5,3}}{G_{5,3}} + \frac{R_{5,5}}{G_{5,5}} \right)}{4} \right] \qquad (3)$$

Blue plane is estimated similar to red plane. To eliminate chrominance distortions, one assumes that color hue varies smoothly in natural images. It defines two `hues' as ratios of each chrominance component to luminance, and assumes that interpolated luminance interpolates these hue values rather than chrominance values to reduce color aliasing.

The cost-effectiveness of a new breed of color filter array patterns based on this sampling theory was highlighted by Hirakawa, [9] detailing an implementation of the demosaicking method consisting of entirely linear elements and comprising a total of only ten add operations per full-pixel reconstruction. With color fidelity that rivals the state-of-the-art interpolation methods and an order of complexity near to that of the bilinear interpolation, this joint sensor-demosaicking solution to digital camera architectures can fulfill the image quality and complexity needs of future digital multimedia simultaneously.

Edge based methods

An influential demosaicking technique using constraint sets to reconstruct a full color resolution channel for Bayer CFA samples was proposed by Jayachandran and Dhanasekaran [10]. The new algorithm produced high frequency image information. This iterative set theoretic reconstruction technique converges to a fixed point that is a solution to demosaicking. Experiments with the proposed method were compared to other latest demosaicking algorithms regarding image quality and PSNR

Methods to improve color artifacts near edges are based on edge-directed interpolation which carries out interpolation along edges instead of across edges, with a gradient set being determined from neighbouring pixels was presented by Jeon [11]. Instead of selecting one direction, weighted-edge methods estimate likelihoods of different edges for weighting one or more directional interpolation and reduce improved color artifacts. Such weighted-edge methods prevent occurrence of color artifacts in demosaicking needing higher implementation cost.

A demosaicking method using high frequency wavelet coefficients as weighting factors was presented by Jeong [12], where low frequency wavelet coefficients were obtained by weighted average. High frequency coefficients were estimated by replacing rules. The proposed wavelet domain demosaicking method was simulated and compared to the new algorithm and to current demosaicking schemes. The Experiments revealed that the new method generated good demosaicking results.

A new method to suppress undesirable artifacts around line edges was proposed by Jeong, [13]. The new method first determines line edge patterns and interpolates missing pixels along detected directions. Experiments proved that the new method produced visually pleasing images, outperformed existing demosaicking methods regarding PSNR.

II. RELATED WORK

A real-time, highly cost-effective approach to image demosaicking targeting high-speed and compact hardware implementation was presented by Karloff and Muscedere [14]. Many current demosaicking methods need multiple processing iterations and complex calculations unsuited for high throughput or compact applications. The new method simplified demosaicking to reduce computational complexity, preserve final image quality and lower memory requirements by removing buffering large image areas for processing.

A new color filter array demosaicking method which emphasized edge estimation was proposed by Kim and Cho [15] for edge estimation, direction using global information, a MRF framework where energy function is formulated through defining new notions of interpolation risk and pixel connectivity. Minimizing this gives edge directions with green channel being interpolated along edges. Then luminance update is iterated and color correction used high frequencies from green channel. The algorithm was tested with commonly used images, and yielded higher CPSNR than state-of-the-art methods in images up to 2.7dB at maximum with the average being 0.4dB. Subjective comparison showed that the new method produced fewer artifacts on complex structures.

A new adaptive CFA interpolation model is proposed by Sree Devi, [16] where if a pixel is not an edge, then the estimation is done using smooth hue transition interpolation. In this review fuzzy logic is applied and the fuzzy rule selection is based on Genetic algorithm and Hybrid GA which uses random local search.

PCA based spatially adaptive denoising of CFA, images use the concept of denoising first and demosaicing later for reducing the noise was highlighted by Sree Devi, [17]. This method effectively suppresses noise while preserving color edges and details. The direct CFA image denoising scheme, followed by a succeeding demosaicing scheme reduces extensively the noise-caused color artifacts in the demosaiced images. The proposed scheme preserves very well the fine structures in the image, which are often smoothed by other denoising schemes and results in the selective removal of noise without blurring sharp edges. The experimental result shows that the proposed method produced better PSNR ratio and less number of noise color artifacts in sample images.

Hybrid use of frequency domain demosaicking with wavelet decomposition post-processing to reduce color artifacts found around the edges was used by Kolta [18]. The algorithm is iterative with an adaptive stopping criterion being suggested. Results revealed improvement regarding visual and numerical comparisons using Peak Signal-to-Noise Ratio (PSNR) between the demosaicked image before and after post-processing.

A new technique to extract true sensor pixel values using blind reverse demosaicking from inferior color image input was proposed by Li and Randhawa [19]. A state-of-the-art demosaicking method was used to reproduce the output image with minimal color artifacts. An advantage of the new blind reverse demosaicking method was that an image not in RAW format (digital negative) could be improved in quality with demosaicking algorithms advancement.

A no-reference quality evaluation method for CFA demosaicking was introduced by Liu [20], where the double interpolation concept was applied. Also, Double Interpolation (DI) scheme could locate interpolation artifacts which make us uncomfortable. Experiments showed that the DI difference map provides local quality assessments and DI PSNR provides a PSNR estimation without ground truth image as a global quality assessment.

Size reduction by interpolation in fuzzy rule bases was proposed by Koczy and Hirota [21] in which dense rule bases were reduced so that only minimal rules containing essential information in original base remain and other rules were replaced by an interpolation algorithm that recovered them with a certain accuracy prescribed prior to reduction. Lagrange method was used for the interpolation method, used for demonstration supplying best fitting minimal degree polynomial. The study concentrated on reduction technique which was independent of the interpolation model style, but is a tractable algorithm.

III. METHODOLOGY

Adaptive CFA interpolation - Smooth Hue Transition Interpolation

In the adaptive CFA interpolation model, all the pixels are divided into normal pixels and pixels in an edge. The smooth hue transition interpolation is utilized when the pixel is not in an edge. The red hue is defined as a ratio between Red and Green colors and Blue hue is defined as a ratio between Blue and green color. Equations [4-6] gives the interpolation of missing blue value at three different locations (m, n). For interpolating missing blue value, the computation is carried out as follows [1, 20].

Case 1: If a pixel at a location (m, n) has only green value and adjacent right and left pixels have the component of blue color, then information of blue color component at the location (m, n) is calculated by,

$$B_{m,n} = G_{m,n} * \left(\frac{B_{m,n-1}}{G_{m,n-1}} + \frac{B_{m,n+1}}{G_{m,n+1}} \right) / 2 \tag{4}$$

Case 2: If pixel at a location (m, n) has only green value and adjacent top and bottom pixels have the component of blue color, then information of blue color component at the location (m, n) is calculated by,

$$B_{m,n} = G_{m,n} * \left(\frac{B_{m-1,n}}{G_{m-1,n}} + \frac{B_{m+1,n}}{G_{m+1,n}} \right) / 2 \tag{5}$$

Case 3: If a pixel at a location (m, n) has only red value, then four diagonals will be a blue color. Then blue color at location (m, n) is calculated by,

$$B_{m,n} = G_{m,n} * \left(\frac{B_{m-1,n-1}}{G_{m-1,n-1}} + \frac{B_{m-1,n+1}}{G_{m-1,n+1}} + \frac{B_{m+1,n-1}}{G_{m+1,n-1}} + \frac{B_{m+1,n+1}}{G_{m+1,n+1}} \right) / 4 \tag{6}$$

Sobel and Canny edge detection methods are used for the detection of pixels at an edge. But the transition of luminance or sharpness is not represented which is essential to perform interpolation. Edge transition based interpolation is useful to avoid the interpolation across the edges and perform interpolation along the direction of edges. In this work, at each pixel of an edge, depending on the correlation of surrounding pixel a mathematical model is proposed. It defines two scenarios, one for a horizontal directed edge and another for a vertical directed edge. Direction is determined by referring the next pixel in the edge was presented by Naveen and Shobanbabu [22]. The new mathematical model is explained by using the example in figure 2. Assume that R is the missing component. Equations [7-9] gives the estimation of red value as horizontal and vertical directed edges.

In the horizontal scenario, If $G_1 > G_2$ then

$$R = 0.075G_1 + 0.025G_2 \tag{7}$$

If $G_3 > G_4$ then

$$R = 0.075G_3 + 0.025G_4 \tag{8}$$

B	G_3	B
G_1	R	G_2
B	G_4	B

Figure 2 Example to find missing Component R

In the vertical scenario, If $G_3 > G_4$ then

$$R = 0.075G_1 + 0.025G_2 + 0.75G_3 + 0.25G_4 \quad (9)$$

Proposed Fuzzy Logic Interpolation

Fuzzy logic is a scientific tool permitting modelling a system sans detailed mathematical descriptions using qualitative and quantitative data. Computations are with words, with knowledge being represented by IF–THEN linguistic rules. An action takes place when a condition is fulfilled. A fuzzy rule-base delivers fuzzy classification consisting of a return value tuple for every considered output class whose values represent class assignment degree Benz et al [23].

Simplest fuzzy rules depend on one fuzzy set. When a condition is fulfilled an action takes place. A fuzzy rule-base delivers fuzzy classification consisting of a tuple of return values for every considered output class whose values represent a class assignment degree. A color interpolation algorithm presented by Tsai, [24] using a method of fuzzy membership assignment along with the concept of smooth hue transition is adaptive in nature and produces superior quality full resolution color image compared to most of the popularly known color interpolation algorithms.

A fuzzy rule-based classification systems consist of two phases of the selection of a small number of fuzzy rules: The first phase is rule generation by data mining criteria and the second one is rule selection by genetic algorithms was proposed by Hisao Ishibuchi [25]. First, a large number of candidate rules are generated and prescreened using two rule evaluation criteria in data mining. Next a small number of fuzzy rules are selected from candidate rules using genetic algorithms. Rule selection is formulated as an optimization problem with three objectives: to maximize the classification accuracy, to minimize the number of selected rules, and to minimize the total rule length.

A small number of simple fuzzy if-then rules can be selected for pattern classification problems with many continuous attributes was shown by Ishibuchi, Yamamoto [26]. Fuzzy rule-based systems were applied to application areas like classification and control. The objectives in design of fuzzy rule-based systems are performance maximization, and comprehensibility. Factors related to fuzzy rule-based systems comprehensibility are:

(i) Fuzzy partitions comprehensibility (number of fuzzy sets for each variable, separation of neighbouring fuzzy sets, linguistic interpretability of a fuzzy set).

(ii) Fuzzy rule-based systems simplicity (number of fuzzy if-then rules, number of input variables).

(iii) Fuzzy if-then rules simplicity (number of antecedent conditions in each fuzzy if-then rule, type of fuzzy if-then rules).

(iv) Fuzzy reasoning simplicity (voting by multiple rules, selection of one winner rule).

Depending upon the correlation amongst the surrounding pixels, a strategy to assign membership grades to the surrounding horizontal and vertical pixels are formed. Equations [10-17] gives the four cases considered, where there is a possible edge along the horizontal and vertical directions.

Case 1:

$|G_1 - G_2|$ is small while $|G_3 - G_4|$ is arbitrarily large, subject to the condition that $|G_3 - G_4|$-$|G_1 - G_2|$ >>0. Here we have assumed the existence of a horizontal edge while the horizontal neighboring pixels G_1 and G_2 have approximately the same intensity.

Case 2:

$|G_1 - G_2|$ is small and $|G_3 - G_4|$ is arbitrary and $G_1 \approx G_2 \approx G_4$. In this case there is also clearly a possible edge of the pixel location R, and the intensity of this edge depends upon the surrounding pixel values G_3 and G_4.

Case 3:

This case is related to case 2, with a difference that here the pixels G_1, G_2 and G_3 to be approximately of similar pixel intensity, i.e. $|G_1 - G_2|$ is small and $|G_3 - G_4|$ is arbitrary and $G_1 \approx G_2 \approx G_3$.

Case 4:

In this case all the four connecting neighboring pixels G_1, G_2, G_3 and G_4 are considered that are all different then location R can be interpolated as follows:

$$\text{Missing } G = \frac{0.5*G_1 + 0.5*G_2 + 0.1*G_3 + 0.1*G_4}{0.5+0.5+0.1+0.1} \quad (10)$$

$$=0.8333*\frac{(G_1+G_2)}{2} + 0.1667*\frac{(G_3+G_4)}{2} \quad (11)$$

For horizontal scenario, if $G_1 > G_2$ then

$$\text{Missing } G = \frac{0.75*G_1 + 0.25*G_2 + 0.1*G_3 + 0.1*G_4}{0.75+0.25+0.1+0.1} \quad (12)$$

$$=0.4167*\frac{(3G_1+G_2)}{2} + 0.1667*\frac{(G_3+G_4)}{2} \quad (13)$$

if $G_3 > G_4$ then

$$\text{Missing } G = \frac{0.5*G_1 + 0.5*G_2 + 0.75*G_3 + 0.25*G_4}{0.75+0.5+0.75+0.25} \quad (14)$$

$$=0.8333*\frac{(G_1+G_2)}{2} + 0.4167*\frac{(3G_3+G_4)}{2} \quad (15)$$

For vertical scenario, when $G_3 > G_4$

$$\text{Missing } G = \frac{0.075*G_1 + 0.025*G_2 + 0.75*G_3 + 0.25*G_4}{0.075+0.025+0.75+0.25} \quad (16)$$

$$=0.0454*\frac{(3G_1+G_2)}{2} + 0.4545*\frac{(3G_3+G_4)}{2} \quad (17)$$

The design of fuzzy rule-based classifiers based on labeled data was approached by combining tools for feature selection, model initialization, model reduction and model tuning was presented by Roubos [27]. It is shown that these can be applied in an iterative way. A covariance-based model initialization method is applied to obtain an initial fuzzy classifier. Successive application of feature selection, rule base simplification and GA-based tuning resulted in compact and accurate classifiers. The proposed approach was successfully applied to the Wine data and results in an accurate classifier that is very compact in comparison with other studies.

Fuzzy rule selection using Genetic algorithms

An optimization method, Genetic algorithm (GA) is inspired by biological systems evolution and is an abstract model of sexual reproduction in a species population where genetic material is modelled by data structure, usually a string of symbols. This is comparable to DNA. Fit individuals in a population survive to reproduce with their genetic material being recombined to new individuals.

Sustainable decision-making ensures complex and ill-defined parameters with high uncertainty due to underlying issues of incomplete understanding. Dynamics of a socio–environmental system is not described by traditional mathematics due to inherent complexity and ambiguity Andriantiatsaholiniaina [28].

Best solutions set is usually kept in an array named population. GA does not need an optimized function to be a mathematical formula, continuous or even derivable. This is the most important factor why they are becoming popular in practical technical optimization. GA forms a type of electronic population, whose members fight for survival, adapting to the environment. GAs use genetic operations like selection, crossover, and mutation to generate solutions that meet given optimization constrains better. Surviving and crossbreeding possibilities are dependent on how well individuals fulfil a target function.

Chromosomes are used to describe the solutions. The test images were created by two different halftoning ways, either using an image bitmap as a genetic algorithm chromosome, or by creating objects, such as lines, letters, rectangles, circles etc., into the image according the parameters encoded to a chromosome was presented by Mantere [29]. Genetic Algorithm is one of the best function optimization methods. The Roulette wheel is a probability based selection technique presented by Meera Kapoor [30]. The fitness function chosen by roulette wheel selection optimization procedure produces better results.

With a population size L, the parameters of each fuzzy model (solution) in a chromosome $\vec{s}_l, l = 1...L$ as a sequence of elements defining the fuzzy sets in the rule antecedents are encoded. A classifier with M fuzzy rules is encoded in equation (18)

$$\vec{s}_l = (ant_1 ... ant_M) \tag{18}$$

Where $ant_i = (a_{i1}, b_{i1}, c_{i1} ... a_{in}, b_{in}, c_{in})$ contains the parameters of the antecedent fuzzy sets $A_{ij}.j = 1...n$.

The roulette wheel selection method is used to select n_C chromosomes for operation. The chance on the roulette wheel is adaptive and is given as $P_l / \sum_{l'} P_{l'}$, where

$$P_l = \left(\frac{1}{J_l}\right)^2, l, l' \in \{1...L\} \tag{19}$$

and J_l is the performance of the model encoded on chromosome $\vec{s}_l$ given in equation (19). In this the GA used is hybridized using local search to avoid local minima.

Local Search

Local search methods use local knowledge for improving solution's chances to propagate characteristics to succeeding generations. A different forms of integration between genetic algorithms and other search and optimization techniques are reviewed by El-Mihoub [31]. Several issues that need to be taken into consideration when designing a hybrid genetic algorithm that uses another search method as a local search tool was examined. Local Search Procedures are optimization methods that maintain a solution, known as current solution, and explore the search space by steps within its neighbourhood. They usually go from the current solution for a better close solution, which is used, in the next iteration, as current solution was explained by García Martínez [32]. This process is repeated till a stop condition is fulfilled. Three important LSPs are:

First Improvement Local Search: Replaces the current solution with a randomly chosen neighbouring solution with a better fitness value.

Best Improvement Local Search: Replaces the current solution with the best among all the neighbouring solutions.

Randomised K-opt LSP (RandK-LS): Looks for a better solution by altering a variable number of k components of the current solution per iteration, i.e. the dimension of the explored neighbourhood is variable.

A hybrid genetic algorithm developed as a combination of a binary genetic and steepest descent gradient algorithm was explained by Boriskin [33]. Here the genetic algorithm performs global exploration of the whole design space aiming at the identification of a given number of promising solutions, whereas SDG algorithm is used to refine these nearly optimal solutions via local down-hill optimization. Such a two-step strategy enables one to significantly reduce stagnation often observed for GAs at the later stage of optimization.

A new and improved CFA demosaicking method to ensure high quality color images and new image measures to quantify demosaicking performance a high resolution color image was introduced by Sree Devi [34]. This study uses an edge indicator function and edge directions are considered in the suggested interpolation method to avoid high frequency region artifacts and improve performance. The first step in the functioning of a GA is the generation of an initial population. Each member of this population encodes a possible solution to a problem. The initial population of size 250 is chosen and each individual is evaluated and assigned a fitness value according to the fitness function. The pseudo code is as follows,

begin

set control parameter μ = 4 and the number of chaotic local search k;

generate a random number range 0 to 1 as y0 and $y0 \notin \{0, 0.25, 0.75, 1.0\}$;

generate chaotic sequences with the length of k according to $x_n = x^j_{best} + (-1)^n y_n$

calculate fitness values of k individuals in POP_n *using objective function;*

find out the individual with best fitness value IND_{nb} *in* POP_n;

if IND_{nb} *is better than* IND_{cb} *then*

$IND_{nw} \leftarrow IND_{nb}$ (*where* IND_{nw} *is the individual with the worst fitness value in* POP_c)

end

IV. EXPERIMENT RESULTS

In this study, a new adaptive CFA interpolation model is proposed. For the pixels in the normal regions of an image Hue transition interpolation technique is used, whereas if a pixel is not an edge, then the estimation is done using an adaptive CFA method. The fuzzy rule selection is based on Genetic algorithm and Hybrid GA which uses random local search is used for color interpolation.

TABLE 1. PSNR FOR SAMPLE IMAGES

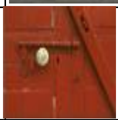
Sl No	Sample Images	R, G, B pixels	Adaptive CFA using Sobel	Proposed Technique with Fuzzy rules	Proposed technique with Fuzzy GA	Hybrid Genetic Fuzzy Algorithm with random local search
1		R	34.49	35.26	35.64	36.03
		G	36.01	36.87	37.34	37.86
		B	34.73	35.55	36.04	36.52
2		R	39.00	40.13	40.66	41.23
		G	42.65	43.65	44.22	44.81
		B	41.24	42.25	42.68	43.20
3		R	41.86	42.99	43.54	44.02
		G	43.69	44.80	45.44	46.01
		B	41.24	42.37	42.82	43.39
4		R	38.05	38.97	39.43	39.99
		G	42.48	43.50	44.11	44.64
		B	41.38	42.34	42.86	43.42
5		R	38.11	39.19	39.61	40.08
		G	39.76	40.72	41.23	41.64
		B	38.82	39.78	40.18	40.68
6		R	36.57	37.44	37.91	38.35
		G	37.71	38.78	39.17	39.59
		B	35.87	36.86	37.25	37.63
7		R	42.81	43.92	44.51	45.05
		G	45.1	46.08	46.71	47.30
		B	43.22	44.2	44.72	45.30

Table 1 gives the PSNR value achieved from various techniques, for sample images 1-7 taken for investigation. Figure 4 (a) is the first sample image and 4 (b), 4 (c), 4 (d), 4 (e) are reconstructed images by adaptive CFA, Fuzzy Technique, Fuzzy rule selection by GA and hybrid genetic fuzzy respectively.

In the reconstructed image, the image is partially shown to highlight the distortion seen. PSNR is the subjective quality comparison method used in interpolation algorithms. Figure 5 shows Red, Green and Blue PSNR values for sample images 1-7 achieved by various techniques. The reconstructed image by proposed technique with hybrid genetic fuzzy GA produces better PSNR. Results are compared with PSNR values obtained by different interpolation methods. For the sample image used in figure 4, the proposed method gives an average PSNR value of 36.80 for RGB components.

Figure 4(a) Original Image

4 (b) Reconstructed image using Adaptive CFA with Sobel

(c) Reconstructed image using Fuzzy technique

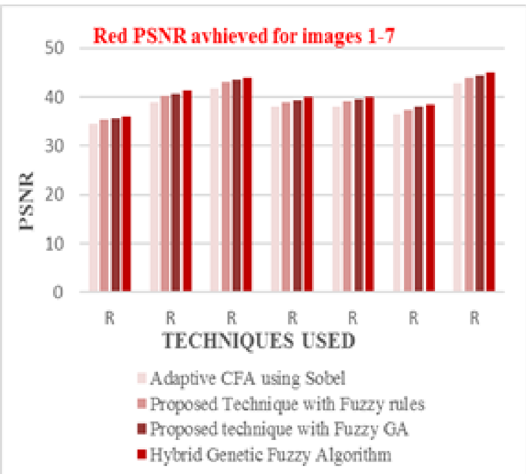
The proposed technique achieves a 1.76% improvement in the PSNR when compared with Adaptive CFA interpolation with Sobel and 0.46% when compared to Fuzzy rule selection using GA. Similarly, for the seventh sample image (parrot image) the proposed method gives an average PSNR value of 45.88 for RGB components.

The proposed technique achieves 2.17% improvement in the PSNR when compared with Adaptive CFA interpolation without fuzzy technique and 0.56% when compared to the proposed technique with fuzzy rule selection using GA. The reconstructed image by proposed CFA produces better PSNR. The results demonstrate the proposed method's efficiency.

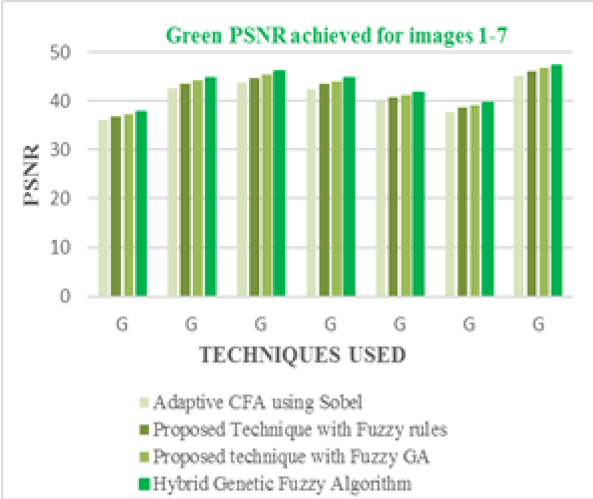
(d) Reconstructed image using Fuzzy rule selection with GA

(e) Reconstructed using image using hybrid genetic Fuzzy technique

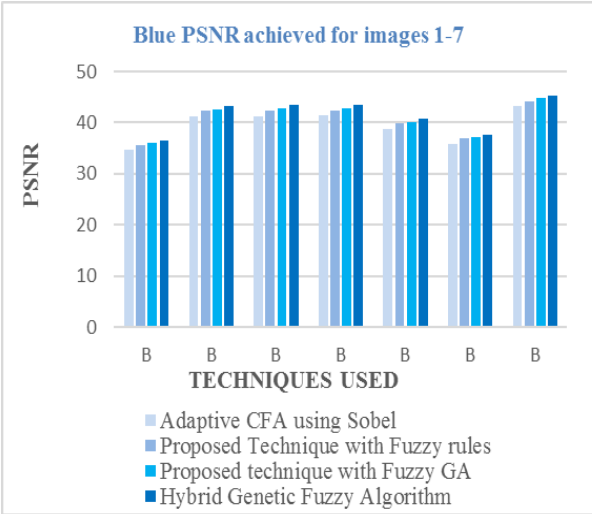
Figure 4(b-e) Reconstructed Image using Adaptive CFA with Sobel, proposed fuzzy technique, Proposed Fuzzy rule selection with GA and Proposed Hybrid Fuzzy technique for sample Image 1



(a) Red PSNR for sample images 1-7



(b) Green PSNR for sample images 1-7



(c) Blue PSNR for sample images 1-7

Figure 5 (a-c) Red, Green and Blue PSNR for sample images 1-7

V. CONCLUSION

In most image capturing devices, region colors are captured with one sensor and a CFA to reduce cost and packaging. CFA acts as a coating on a sensor array pixel that allows a color component's photon and blocks photons of the other two color components. So, a process called as interpolation is required to get missing colors. Most interpolation algorithms fail on edges. To offset this, a new adaptive CFA interpolation model is proposed in this work. For normal regions pixel in an image Hue transition technique is used, whereas for edge pixels the proposed mathematical model is used with edge transition information.

The fuzzy rule-based system design objectives are performance maximization, and comprehensibility. This work uses fuzzy logic to form interpolation rules. Fuzzy rule selection is achieved using GA with random local search. Efficiency of the new method is higher when using Green plane interpolation, Red and blue plane interpolation with the fuzzy genetic method for interpolation.

Seven sample images were taken and reconstructed by Adaptive CFA using Sobel, CFA interpolation technique with Fuzzy rules, Fuzzy rule selection with genetic algorithm and finally the proposed hybrid genetic fuzzy interpolation with random local search. The PSNR was evaluated for different techniques. It was observed that the proposed Adaptive CFA using hybrid genetic fuzzy interpolation with the random local search approach produced images with high visual quality.

An improvement of PSNR can be achieved by the proposed hybrid genetic fuzzy system with a random local search method. The experimental results reveal that the new method achieves better Red, Green and Blue PSNR values compared with other techniques used for the sample images taken.

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