International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 4 Issue 6, September-October 2020 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Gaussian Fuzzy Blocking Artifacts Removal of High DCT Compressed Images

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ABSTRACT

A new artifact removal method as cascade of Gaussian fuzzy edge decider and fuzzy image correction is proposed. In this design, a highly compressed i.e. low bit rate image is considered. Here, each overlapped block of image is fed to a Gaussian fuzzy based decider to check whether the central pixel of image block needs correction. Hence, the central pixel of overlapped block is corrected by fuzzy gradient of its neighbors. Experimental results shows remarkable improvement with presented gFAR algorithm compared to the past methods subjectively (visual quality) and objectively (PSNR).

KEYWORDS: *Fuzzy logic; Image Coding; Image Compression; Blocking Artifacts*

***How to cite this paper**:* Deepak Gambhir "Gaussian Fuzzy Blocking Artifacts Removal of High DCT Compressed Images" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-4 | Issue-6, October 2020, pp.269-274, URL: www.ijtsrd.com/papers/ijtsrd33361.pdf

IJTSRD33361

I. INTRODUCTION

Joint Photographic Experts Group (JPEG) has been designed as a compression method for continuous-tone images. The main goal of JPEG compression is to achieve high compression ratios, however to achieve high CRs, JPEG results in certain degradations in the reconstructed images. Images are frequently transformed to frequency domain via DCT etc. for further processing/enhancement specifically in the case of DCT image processed as blocks. In standard image compression process these DCT transformed blocks are quantized block-by-block with the standard quantization matrix. This process of quantization varied from small to large quantization matrix, resulting in compression from high bit-rate to low-bit rate respectively. The extremely low bit-rate kind of compression certainly results to visually annoying degradations in the image known as 'blocking artifacts'.

In DCT coding process, the image is first divided into square blocks of 8 x 8 pixels. Each block is then transformed by means of DCT. The DCT coefficients are quantized and finally encoded to create binary data output stream. Blocking effect in DCT coded images appears as boundaries between adjacent blocks that are visible for low bit-rates [1]. This kind of degradation is highly objectionable, and affects the quality judgment of the final observer [2]. Blocking artifacts appears due to quantization of low-frequency coefficients giving rise to discontinuity between intensities of two adjacent blocks [15].Many deblocking approaches have been proposed in still image coding. An adaptive separable median filter was proposed by Hsu and Chen [3] as a post-filter to reduce blocking effects generated at low-bit rate.

The key idea is to represent every known property of the original image by closed convex set. POCS-based image recovery algorithm has two requirements: defining a closed convex constraint sets and Projections onto these constraint sets. Two types of constraint sets used in the recovery algorithms are constraint sets based on the transmitted compressed image and the constraint sets based on a priori knowledge about the original image [12]. Zakhor uses a set of band-limited images, and the corresponding projection is performed by a low-pass filter. Blocking artifacts are significantly reduced, but some blurring is introduced that cannot be prevented by the quantization constraint. This is mainly because the quantization constraint defines a set that is too large, containing among others, both the original and the blocky image. The POCS approach by Yang and Galatsanos [5] defines the smoothness set as the set of all images for which the sum of the squared pixel differences across block boundaries is smaller than a specified value. The approach also considered that the compression artifacts in image are spatially varying.

Liu and Bovik [6] proposed a DCT-domain method for blind measurement of blocking artifacts, by modeling the artifacts as 2-step functions in shifted blocks. Zeng [7] proposes a simple DCT-domain method for blocking effect reduction, applying a zero masking to the DCT coefficients of some shifted image blocks. This DCT- domain method provides DCT transform domain solution to reduce the effects of blocking artifacts. However, loss of edge information caused by the zero-masking scheme is noticeable. Luo and Ward [8] and Singh et al. [9] gave a new approach which preserved the edge information. These methods are based on reducing the blocking artifacts in the smooth regions of the image. The correlation between the intensity values of the boundary pixels of two neighboring blocks in the DCT domain is used to distinguish between smooth and non-smooth regions.

A recent artifact removal scheme is proposed by Kim and Sim [11] based on adaptive adjustment of weights according to the directional correlation and activities of local areas. The proposed approach for the spatial smoothing applies the Signal Adaptive Weighted Sum (SAWS) technique to the current pixel and boundary pixels. Moreover, a Strength Parameter (SP) is applied to weights to avoid excessive blurring in the detailed area. The deblocking process is weak in the detailed area however strong in smooth area.

The rest of paper proceeds as follows: Section I describes the General model of blocking artifacts. In Section II the discussion on basics of fuzzy logic is presented. Section III presents the details about Gaussian membership based on fuzzy classification of blocks. Section IV presents proposed (gFAR) method of fuzzy blocking artifact removal and section V concludes results and discussion.

II. GENERAL MODEL OF BLOCKING ARTIFACTS AND ITS IMPLEMENTATION [10]

Low bit rate quantizes most of the DCT coefficients to zeros. The blocking effects in the horizontal and vertical directions generally impact the image. Therefore, the formulation of blocking artifacts is as follows:
Suppose i_1 and i_2 are image values of two pixels adjacent to each other in same row or column, but are in different blocks. It is assumed that blockiness of the compressed image is related to the fact that before compression the values of i_1 and i_2 were usually similar, but the quantization makes the values more different. Hence edge variance E is defined as the sum of the squared differences for all such pixel pairs.

$$E = \sum [i_1 - i_2]^2 \quad (1)$$

The block edge variance E is a measure of image blockiness.

The desired value of the edge variance is estimated if the same measure for the pixels inside the edge on either side is computed and then average is calculated. If the estimated value is less than the edge variance, the edge variance is tried to be reduced, adjusting the edge variance in this way alters only the edge pixels. The reduction done in the direction of the gradient of edge variance may not be completely achieved if the minimum reduction in this direction is above the next-to-edge variance. The problem gets reduced at the boundary however; a new problem has been created inside the blocks. Then the attempt is to reduce this problem by monitoring a measure of image roughness in the blocks.

For natural images, each block is modeled as a constant block distorted by i.i.d (independent, identically distributed noise), i.e. white noise with zero mean and a small variance [7]. Consider two adjacent (either vertical or horizontal) 8x8 blocks x_1, x_2 with its average values as $\bar{a}$ and $\bar{b}$, respectively. Thus, these two blocks can be modeled as follows:

$$x_1 = \bar{a} + \varepsilon_{i,j} \ , \ x_2 = \bar{b} + \delta_{i,j} \quad (2)$$

Where, $\varepsilon_{i,j}$ and $\delta_{i,j}$ are modeled as i.i.d. white noise blocks with zero mean. Hence an overlap block can be composed of the half of x_1, and the half of x_2 to constitute a new 8x8 block *x* as shown in Fig. 1.

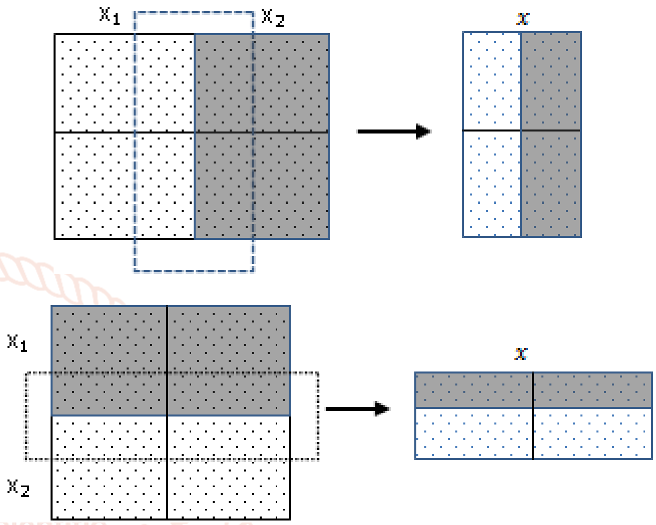

Fig. 1: Structure of a new block x, consisting of x_1 and x_2 (either left and right or up and bottom)

Then, a 2-D step function in the block x defined as follows:

$$st = -\tfrac{1}{2}; \text{ left or bottom half of block } x \quad (3)$$

$$st = \tfrac{1}{2}; \text{ right or top half of block } x \quad (4)$$

The new block may be modeled as follows:

$$x = |S| * st + \mu + B \quad (5)$$

where, |S| represents the amplitude of 2-D step function st, B is the average value in the block x, this is represented as the local background brightness, and μ is a white noise with zero-mean, defined as the local activity around the block edge. The larger is the value of |S|, more serious are the blocking artifacts, if the background brightness and local activity remains unchanged. If the value of | S | is estimated the blocking artifacts between two blocks is measured.

III. UNDERSTANDING BASICS OF FUZZY LOGIC

The concept of fuzzy logic deals with the partial truth or partial false whereas binary logic concept is of either true or false. A fuzzy set is a class of objects characterized by a membership function. Each object is assigned a grade of membership ranging between 0 and 1[13]. Instead of having no or complete membership in set, fuzzy set refers to elements in the set having partial membership. Suppose an example of fuzzy logic is considered: A set of bright pixels in gray scale image is to be classified with respect to dull pixels. When this set is defined in binary logic, the values more than 150 are classified as bright pixels and less than 150 as dull pixels. However it is not reasonable to consider value of 150 as bright pixel and value 149 as dull pixel. Whereas in contrast with fuzzy logic, values less than 50 is dull and values greater than 150 are bright and values between 50 and 150 is considered to have partial membership in bright and partial membership in a dull set.

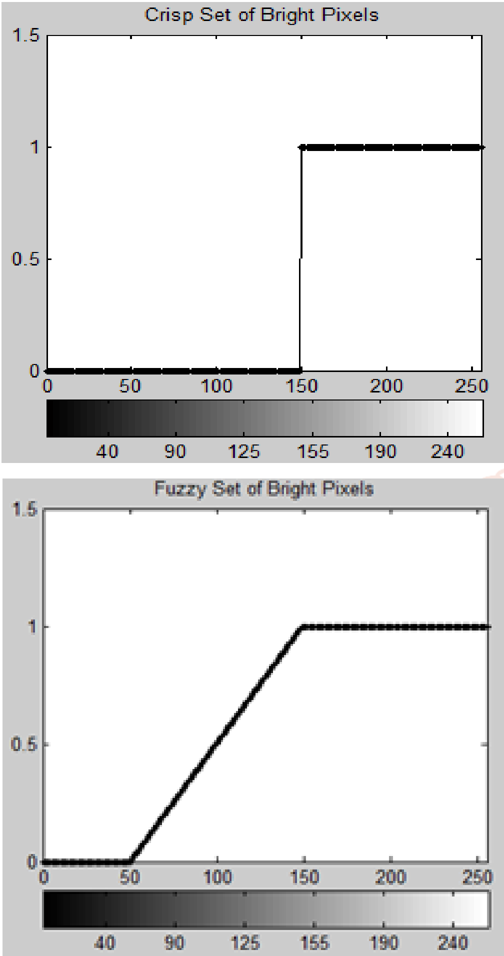

Fig. 2: Membership functions for set Bright Pixels

IV. GAUSSIAN MEMBERSHIP-BASED FUZZY CLASSIFICATION OF BLOCKS [10]

A gray-tone image X is considered of R x C dimension. A histogram-based fuzzy membership function is defined to represent pixels of the spatial domain image sub-matrices called block to the fuzzy domain image block

$$\mu_{i,j} = G(x_{i,j}) = e^{\frac{-(B_{\max} - x_{ij})^2}{2\sigma_f^{\,2}}} \qquad (6)$$

Where, G (x_{ij}) is a Gaussian function, and B_{max}, x_{ij} are the maximum and (i, j) th gray values respectively in a block and the fuzzifier σ_f. The fuzzifier σf defines the width of the Gaussian function. The only fuzzifier σ_f can be defined as:

$$\sigma_f^{\,2} = \frac{\sum_{k=0}^{L-1} (B_{\max} - k)^4 \, p(k)}{2\sum_{k=0}^{L-1} (B_{\max} - k)^2 \, p(k)} \qquad (7)$$

Where, k represents certain gray level in the range [0 to L-1].

Here a fuzzy histogram is obtained as the frequency of occurrence of membership functions of gray levels in the fuzzy image. Thus,

$$X = \bigcup \{\mu(x), p(x)\} = \left\{ \mu_{i,j} / x_{i,j} \right\};$$
$$i = 1,2,3\ldots.., R;\ j = 1,2,3\ldots.., C \qquad (8)$$

Where, μ(x) is the membership of pixel with intensity value of x, and p(x) is the number of occurrences of the intensity value x, in an image X. The distribution of p(x) is normalized such that

$$\sum_{x=0}^{L-1} p(x) = 1 \qquad (9)$$

The term p(x) represents the frequency of occurrence of x in histogram X.

In this theory of fuzzy plane, a contrast-enhanced image block is said to be low perception (dark) for μ [0, 0.5] or high perception (bright) for μ [0.5, 1] values. This leaves pixels near μ = 0.5 having the highest ambiguity and do not belong to either perception class. Hence these can be treated as pixels which describe the fuzzy boundary. Thus, a range of values μ for a block near 0.5 is considered to contain edges, the range of values between 0.45 - 0.55 requires correction.

V. PROPOSED ALGORITHM

The understanding of general model of Blockiness and the Gaussian memberships values (described previously) are used to judge the degree of edginess present in block. Then, the membership values are found for the restoration on pixel by pixel basis. The filtering methods proposed by Fuzzy based approaches uses local information of the image, these fuzzy filters have good edge preserving property and apply filtering to the corrupted blocks and its neighbors [14].

The proposed (Gaussian Fuzzy Artifacts Removal) algorithm is:

1. Take a highly compressed DCT artifact Image and obtain an overlapped N x N block out of it.
2. Fed each N x N block to a Fuzzy detector so as to decide about edge intensity of the blocks based on the Gaussian based membership function.
3. The membership degree of each pixel in the block is computed as:

$$\mu_{i,j} = G(x_{i,j}) = e^{\frac{-(B_{\max} - x_{ij})^2}{2\sigma_f^{\,2}}} \qquad (10)$$

This Gaussian membership function uses mean as the maximum value of block (B_{max}) and the variance σ_f varies with block intensity values.

Rule: In general if most of the memberships of these pixels represent the value around 0.5, then block considered is an edge block and needs to be corrected.

4. The restoration of central pixel of these selected edge blocks is performed on the basis of its neighbor

intensity, firstly the maximum absolute intensity difference of the central pixel about its neighbors is computed as:

$$D_{\max} = \max\{|I(i+k, j+l) - I(i,j)|\} st(k,l) \in block \quad (11)$$

This maximum absolute intensity difference of the central pixel about its neighbors: D_{max} is used to compute the fuzzy membership of the central pixel as:

$$\mu = \begin{cases} 0; D_{\max} > THR_A \\ \dfrac{D_{\max} - THR_A}{THR_A - THR_B}; THR_A < D_{\max} < THR_B \\ 1; D_{\max} < THR_B \end{cases} ; \quad (12)$$

Where THR_A and THR_B are two predefined thresholds and have values around mean of a complete image and needs to be preset.

5. Finally the restoration of central pixel of the block is given as:

$$\tilde{I}(i.j) = (1-\mu) * I(i,j) + \mu * D_{\max} \quad (13)$$

This process is repeated for each overlapped block and central pixel is corrected as per need.

The block diagram of proposed gFAR algorithm process is described in Fig. 3

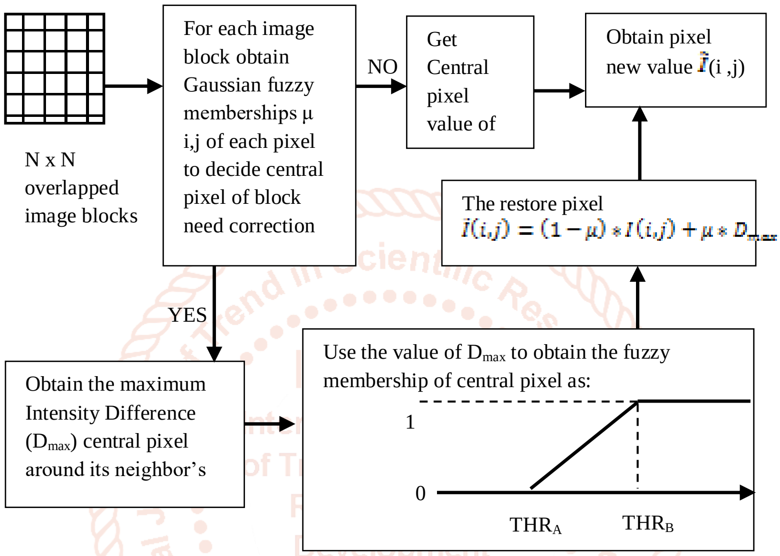

Fig 3: Proposed gFAR Algorithm.

VI. SIMULATION RESULTS AND DISCUSSION

These test images are initially compressed at low bit-rates using the baseline JPEG standard and the image blocking artifacts are generated. To demonstrate the performance of the proposed algorithm experimental results of the proposed method are presented subjectively and objectively as well as also on the computational load. Experiments were conducted using the images such as Lena, Peppers and Goldhill of size 256 x 256 with 256 gray levels.

The objective metric used for comparison of original image I and restored image Ĩ is the PSNR (Peak Signal-to-Noise Ratio) and the MSE (Mean Square Error) value. In general, the larger is PSNR (dB) value; the better is the reconstructed image quality. The mathematical formulae for the computation of MSE & PSNR is

$$MSE = \sum_{m-1}^{M} \sum_{n=1}^{N} \left[pix_{org}(m,n) - pix_{decomp}(m,n) \right]^2 \quad (14)$$

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \quad (15)$$

(a) (b) (c)


(d)


(e)


(f)


(g)


(h)


(i)

(a) Original Image (b) JPEG compressed at Q=1 (c) JPEG compressed at Q=3
(d) gFAR at Q=3 (e) SAWS at Q=2.5 (f) gFAR at Q=2.5
(G) SAWS AT Q=3 (H) JPEG COMPRESSED AT Q=2 (I) GFAR AT Q=2

TABLE I. MSE (MEAN SQUARE ERROR) AND PSNR (PEAK SIGNAL NOISE RATIO) COMPARISON FOR Q = 2

256 X 256	JPEG		SAWS [11] with SP		gFAR Proposed	
	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)	MSE
Lena	25.11	200.35	31.24	48.87	42.96	31.80
Goldhill	24.26	243.67	28.65	87.64	28.77	86.36
Peppers	25.22	195.47	31.36	47.55	32.22	39.04

TABLE II. MSE (MEAN SQUARE ERROR) AND PSNR (PEAK SIGNAL NOISE RATIO) COMPARISON FOR Q = 2.5.

256 X 256	JPEG		SAWS [11] with SP		gFAR Proposed	
	PSNR (dB)	MSE	PSNR(dB)	MSE	PSNR (dB)	MSE
Lena	26.11	159.24	30.08	56.07	31.05	51.07
Goldhill	25.45	185.60	28.17	99.06	28.19	98.61
Peppers	24.39	236.09	30.68	55.62	31.36	47.49

TABLE III. MSE (MEAN SQUARE ERROR) AND PSNR (PEAK SIGNAL NOISE RATIO) COMPARISON FOR Q = 3.

256 X 256	JPEG		SAWS [11] with SP		gFAR Proposed	
	PSNR (dB)	MSE	PSNR(dB)	MSE	PSNR (dB)	MSE
Lena	28.50	91.85	30.11	63.32	30.43	58.78
Goldhill	27.93	104.73	27.74	109.48	27.73	109.71
Peppers	28.92	83.58	30.14	62.95	30.66	55.85

From the results it is very clear that, the SAWS based adaptive weight adjustment recent method introduces blurring in the resulted image whereas the gFAR provides good results over the the exisiting methods.

VII. CONCLUSION

The gFAR algorithm for artifact removal of DCT compressed images has been introduced in this paper. A kind of Gaussian membership value based decision is used to find whether the overlapped block central pixel need correction. Thus further it is corrected using fuzzified values of max gradient and original. The results prove that this fuzzy logic based artifact removal gFAR method gets effective performance in terms of PSNR, MSE as compared to several existing techniques to the date.

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