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Reduction of Artifacts in Jpeg Images with Genetic Algorithm and Boundary Pixel Replacement

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Abstract: Many multimedia applications require image compression with high compression ratio to overcome the difficulties in dealing huge volume of image data. At high compression ratios, the error introduced by quantization of the transform coefficients produces visually undesirable patterns known as compression artifacts that dramatically lower the perceived quality of a particular image. Blocking artifacts of JPEG images and ringing artifacts of JPEG 2000 images plays crucial role in many applications. A great deal of effort has been invested in attempts to solve this problem while preserving the information content of the image. Proposed research primarily concentrates on the blocking artifacts of JPEG images and to a degree over the ringing artifacts of JPEG 2000 images. There exist three different approaches to reduce the artifacts as Preprocessing, Post processing and Transform domain techniques. Recently, attention is diverted to optimize the solution. To enhance the performance of the algorithm principally, the artifacts are to be detected. This in turn needs some metrics to measure these distortions. The metrics used commonly for measuring these distortions are Mean Square Error (MSE) and SNR (Signal to Noise Ratio). Current research computes the measure of blocking artifacts with the new parameter named as Total Blocking Error (TBE). Minimization of TBE is an indication about the elimination of the artifacts. This can be implemented in Transform domain with a modified quantisation table and filter. Efficient suppression of artifacts can be controlled by the scaling parameter in the quantisation process and by the kernel in the filtering process. Hence the problem can be stated as finding an optimal solution for the suppression of Artifacts with these two processes. Genetic Algorithm (GA) is one of the emerging optimization techniques. So far GA has not been used for the optimization of the reduction of artifacts. Hence an attempt is made to optimize the kernel of the filter and the scaling parameter of the quantizationwith GA. A spatial domain algorithm can enhance further the quality of the image by preserving fine details. A spatial domain algorithm can enhance further the quality of the image by preserving fine details. Dynamic range processing divide the image into luminance and chrominance component and converted to a reduced range with logarithmic mapping. Attenuating the magnitudes of large gradients processes gradient field of the luminance image. Solving a poisson equation on the modified gradient field preserves fine details. Finally the integrated in formations are remapped to the original dynamic range with inverse logarithm.

Key words: Genetic algorithm, artifact reduction, DCT, adapted Q, JPEG, TBE

INTRODUCTION

Chang, Kang (2005) presented a fast and systematic scheme to classify the edge orientation of each block in Discrete Cosine Transform (DCT)-compressed images. It is a non-iterative post processing algorithm with two-steps: low-pass filtering and then predicting. Predicting the original image from the low-pass filtered image is performed with less arithmetic operations. Lee *et al.* (2005). constructed the model based on a broken line regression. Averbuch and Zheludev (2004) designed a new family of biorthogonal wavelet transforms and describes their applications to still image compression. The wavelet transforms are constructed from various types of interpolator and quasi interpolator's splines in a fast lifting mode. Proposed method by Shukla *et al.* (2005) approximates the signal segments using polynomial models and utilizes an R-D optimal bit allocation strategy among the different signal segments. The scheme further encodes similar neighbors jointly to achieve the correct exponentially decaying R-D behavior. The inverse half toning algorithm is used to reconstruct a gray image from an input halftone image. Based on the recently published Lookup Table (LUT) technique, Chung and Wu (2005) presented a novel edge-based LUT method for inverse half toning, which improves the quality of the reconstructed gray image.

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Dubbed Recovery of Image Blocks using the Method of Alternating Projections (RIBMAP), is developed by Park. *et al.* (2005) for block-based image and video coders. The algorithm is based on orthogonal projections onto constraint sets in a Hilbert space. Algorithm implemented, by Huang and Salama (2005) using global motion estimation and compensation techniques for boundary recovery, consists of three steps: Boundary extraction from shape; boundary patching using global motion compensation and boundary filling to reconstruct the shape of the damaged video object planes. Park considers the problem of recovering a high-resolution image from a sequence of low-resolution DCT-based compressed observations. Park *et al.* (2004). The DCT quantization noise is analyzed and a model in the spatial domain is proposed as a colored Gaussian process. According to the statistical properties of natural images and the properties of human perception, a constant insensitivity makes sense in the spatial domain but it is certainly not a good option in a frequency domain. Gomez-Perez G *et al.* (2005) made a fixed low-pass assumption, as the number of DCT coefficients to be used in the training was limited. Algorithm instigated by Averbuch *et al.* (2005). Apply weighted sums on pixel quartets, which are symmetrically aligned with respect to block boundaries. This scheme is referred to as Weight Adaptation by Grading (WABG).

Approach by Seungjoon Yang *et al.* (2001) and others employs a parameter-estimation method based on the k-means algorithm with the number of clusters determined by a cluster-separation measure. Gunturk *et al.* (2002) approach is also capable of incorporating known source statistics and other reconstruction constraints to impose blocking artifact reduction and edge enhancement as part of the solution. Another effort by him Bahadir *et al.* (2004) uses DCT-domain Bayesian estimator to enhance resolution in the presence of both quantization and additive noise. Stochastic framework quantization information as well as other statistical information about additive noise and images is utilized. He Bahadir *et al.* (2002) also made use of multi frame constraint sets to reduce blocking artifacts in an alternating-projections scheme. By combining an adaptive binary arithmetic coding technique with context modeling, Detlev Marpe *et al.* (2003) and others achieved a high degree of adaptation and redundancy reduction. Chengjie and Trac (2002) presents a simple, fast and efficient adaptive block transform image coding algorithm based on a combination of pre filtering, post filtering and high-order space-frequency context modeling of block transform coefficients. A novel frequency-domain technique for image blocking artifact detection and reduction is presented by George *et al.* (2002). The algorithm first detects the regions of the image which present visible blocking artifacts. This correction of each DCT coefficient depends on the eight neighboring coefficients in the subband-like representation of the DCT transform and is constrained by the quantization upper and lower bound. Jinshan *et al.* (2003) implemented artifact reduction algorithm based on the contrast measure defined within the discrete cosine transform domain. The advantages of the psycho physically motivated algorithm are used and the compression ratio remains unaffected. The previous contrast domain concepts was extended with inter and intra quantisation for moving images by Fullerton and Peli (2005), Ricardo, (1998) presented techniques for scaling, previewing, rotating, mirroring etc with the goal to reduce compression artifacts.

The compressed images with wavelet still suffer from obvious distortions around sharp edges, which are perceptually objectionable. A model-based edge-reconstruction algorithm for recovering the lossy edges in coded images is proposed by Guoliang Fan and Wai-kuen Cham (2000). Costa and Veiga (2005) generated an optimized quantization table with the JPEG standard suited for each class of images and of different sizes. Yen *et al.* (2005) present a voting strategy to determine a set of morphological filters to be used for reducing the ringing artifacts. All this processing is performed at the encoder side and the set of selected filters are conveyed to the decoder in the form of side information. Next algorithm based on an adapted total variation minimization approach constrained by the knowledge of the input intervals to which the unquantized cosine coefficients belongs is depicted by François *et al.* (2005). Lee *et al.* (2006) developed a simple and efficient algorithm for dynamic range compression and contrast enhancement of digital images in the compressed domain. Tsaig *et al.* (2005) research, explores the use of optimal decimation and interpolation filters in this coding scheme. This optimization problem is solved using the variable Projection method. An alternative method suggested by Triantafyllidis *et al.* (2002) first reconstructs the DCT coefficients based on their observed probability distribution. A spatial filtering step with kernels adapted to local signal further removes block discontinuity, at the same time enhances lines and edges. Minami and Zakhor (1995)

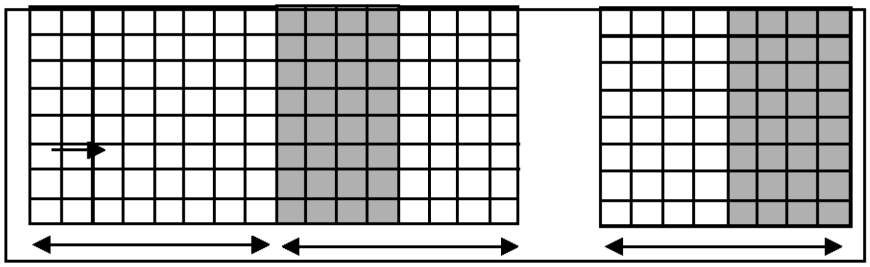

Fig. 1: Model of blocking artifact in the horizontal direction

presented a new approach by minimizing a new criterion called Mean Squared Difference of Slope (MSDS), while imposing linear constraints corresponding to quantisation bounds. Here authors approach depends on the Gradient Projection method, modulated by steepest descent for unconstrained problems. Algorithm devised by Aria, (2002) counter intuitively employs further compression to achieve image enhancement, which is not widely known or not entirely new. FengGao *et al.* (2004) addresses the problem of reducing blocking effects in transform coding using gradient flow with multiple constraints.

A space-variant filter that adapts to local, characteristics of the signal is proposed by Ramamurthi and Gershoin (1986) The algorithm distinguishes edge pixels from non-edge pixels via a neighborhood testing and then switches between a one–dimensional (1-D) and a two–dimensional (2-D) filter accordingly to reduce blocking effects. Another novel method (Aria, 2001), simply re-applies JPEG to the shifted versions of the already-compressed image and forms an average Ivan and Tomas (2005) approach, despite its simplicity, offers better performance and consists of edge adaptive diffusion process before DCT-JPEG compression. Preprocessing helps in preserving the true contours. A graphical user interface measures aid the user in selecting the optimal quantization values with respect to image fidelity and compression ratio for a particular class of images is depicted by Berman *et al.* (1993) Shen and Kio (1997) discussed the principle of compression artifacts, survey of several algorithms that reduce compression artifacts and the current bottleneck and future are done in this research.

MODEL OF BLOCKING ARTIFACT

Consider two adjacent 8*8 blocks A and B as shown in Fig. 1a with average values μ1 and μ2, respectively, where μ1 # μ2. Mathematically blocks are represented as

$$b1 = \mu 1 + \varepsilon_{i,j}\ ;\ b2 = \mu 2 + \delta_{i,j} \qquad (1)$$

where $\varepsilon_{i,j}$ and $\delta_{i,j}$ are modeled as variance of white noise with zero mean. DCT transformation of the block A of an image can be written as Q_A

where k, l = 0,1, ……… 7 = 1/√ v2 and c(k) = 1 for k>0.

When the DCT blocks A and B are
quantized using a large Quantisation parameter, most of the DCT coefficients become zero, which reduces the effect of the variance. As a result, a 2-D step function between A and B may become visible, creating a blocking artifact. Based on this observation, new shifted block C composed of the right half of A and the left half of B is formed as shown in Fig. (1b). DCT coefficients of this block can be computed in the same manner as that of A. The blocking artifact between blocks A and B can be modeled as a 2-D step function in the block b(n). This step function of the new block can be mathematically expressed as

$$s(i,j) = \begin{cases} 1/8, - & i = 0,1,2.....7;\ j = 0,1,2,.......3 \\ 1/8, & i = 0,1,2.......7;\ j = 0,1,2,.......3 \end{cases} \qquad (2)$$

Therefore

$$bn\,(i,j) = \beta\,.s\,(i,j) + \mu + r(i,j);\ i,j = 0,1,2......7 \qquad (3)$$

where |β|, is the amplitude of the 2-D step function, μ is the average value of the block C, indicating the local background brightness and r is the residual block, which describes the local activity around the block edge. Mathematically in one way, removal of artifact is equivalent to converting this step function into a linear function.

DETECTION OF BLOCKING ARTIFACTS

Since blocking artifacts appear across block boundaries, boundary pixels are more focused. After the BDCT transform, a decoded image with blocking effects is expressed as a set of sub matrices. Here Xi,j is an 8* 8 sub matrix. Last and first column of each and every block is manipulated to detect vertical blocking effects of the image and the corresponding rows for the detection of horizontal blocking artifacts.

Vertical blocking artifacts: Let $X_{i,j}(:,1)$ and $X_{i,j}(:,8)$ represents the first and last column of the submatrix $X_{i,j}$. Difference between the last column of the n^{th} block and the first column of the $n+1^{th}$ block is a measure of the vertical blocking effect and known as column difference. All column differences together form the column edge difference vector V_c. V_c^1 represents column differences in between different blocks with the first row sub matrices. Mathematically this can be expressed as

$$V_c^1 = \{[X_{1,1}(:,8) - X_{1,2}(:,1)], [X_{1,2}(:,8) - X_{1,3}(:,1)], \ldots [X_{1,n-1}(:,8) - X_{1,n}(:,1)]\} \quad (4)$$

In the same manner second column sub matrices edge difference can be computed as

$$V_c^2 = \{[X_{2,1}(:,8) - X_{2,2}(:,1)], [X_{2,2}(:,8) - X_{2,3}(:,1)], \ldots [X_{2,n-1}(:,8) - X_{2,n}(:,1)]\}, \quad (5)$$

In order to make it as a column vector take transpose both for inner and outer matrices. Now the column edge difference vector can be computed from these difference values as

$$V_c = \{ V_c^1, V_c^2, V_c^3, \ldots\ldots\ldots V_c^n \} \quad (6)$$

Norm of V_c gives a measure about the blocking effects in the column direction. Likewise the row edge difference vector is computed as V_r.

Horizontal blocking artifacts: Let $X_{i,j}(1,:)$ and $X_{i,j}(1,:)$ represents the first and last row of the submatrix $X_{i,j}$. Row edge difference vector of the first column sub bocks is expressed as

$$V_r^1 = \{[X_{1,1}(8,:) - X_{1,2}(1,:)], [X_{1,2}(8,:) - X_{1,3}(1,:)], \ldots [X_{1,n-1}(8,:) - X_{1,n}(1,:)]\} \quad (7)$$

$$\text{So, } V_r = \{ V_r^1, V_r^2, V_r^3, \ldots\ldots\ldots V_r^n, \} \quad (8)$$

Norm of V_r gives a measure about the blocking effects in the row direction. The total blocking edge value depends on the norm of row and column edge difference vector. New metric is named as Total Blocking Error (TBE). This parameter is directly proportional to both column and row edge difference vectors. Hence it can be stated that TBE is proportional to (norm of V_r + norm of V_c) or

$$TBE = a_1 \mid V_c \mid + a_2 \mid V_r \mid, \quad (9)$$

where a_1 and a_2 are the proportionality constants. From the above analysis it is clear that V_c and V_r provide all the information about the edge differences between any two neighboring blocks of the decoded matrix X. Hence TBE can be used to measure the blocking effects. The larger, TBE, the greater the blocking effects. Filters can be effectively used to minimize these artifacts which in turn reduce TBE. Assume f as the image vector of X. Total image edge vector V_e is expressed as

$$V_e = \{[X_{1,1}(:,8, X_{1,2}(:,1), X_{1,2}(:,8), X_{1,3}(:,1), \ldots X_{1,n-1}(:,8), X_{1,n}(:,1)]^T, [X_{1,1}(8,:), X_{1,2}(1,:), X_{1,2}(8,:), X_{1,3}(1,:), \ldots X_{1,n-1}(8,:), X_{1,n}(1,:,)]^T\} \quad (10)$$

Problem definition: Let us pass the image through a filter H and obtain the new image. Scientifically it can be written as

$$f\,new = H * f \quad (11)$$

where H is the filter, f is the image vector and fnew is the new image vector. The corresponding edge differences are computed as $V_{c\,(cap)}$ and $V_{r\,(cap)}$ and to be compared with the constraint values °1 and $°_2$ respectively. This can be further simplified by TBE with a constraint $°_3$. Objective of the proposed algorithm is to design an optimal spatial filter H such that the new image vector is close to the old image vector with the property of making the block boundaries smooth and improving the quality of the encoded image X. It is expected that once H is designed, the new image vector is obtained and the new reconstructed image is close to the old decoded image X with an improved signal to noise ratio. Above idea is formulated as a typical optimization problem: Given a decoded image X and f as its corresponding image vector, find a matrix filter H such that total blocking error is minimized

$$\min \| H\,fnew - f \|^{2H} \quad (12)$$

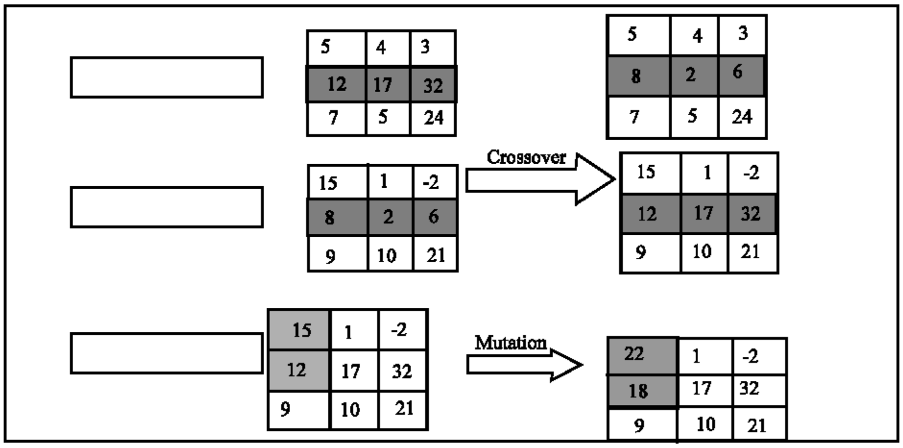

Fig. 2: Structure of chromosome and its genetic operators

IMAGE ENHANCEMENT BASED ON GENETIC ALGORITHM

For the correct feature extraction, the quality of the image should be improved by using appropriate image filters. The number of constructing an ordered subset of n filters from a set of m filters is given by m*n. Trying all cases to find out the best one practically impossible when there are lots of filters available. In this study, GA is used to search filters of the proper type and order. In each generation, the fitness of chromosome is evaluated by using the fitness function and chromosomes with higher fitness are stochastically selected and applied with genetic operators such as crossover and mutation to reproduce the population of the next generation. Elitist-strategy that always keeps the best chromosome found so far is used. Chromosomes are represented as simple numbers corresponding with individual filters kernel. Figure 2 shows the structure of chromosomes and the examples of genetic operators such as crossover and mutation.

Fitness function definition and crossover selection: The fitness function in the designed genetic algorithm compares responses with TBE. The edge differences are then summed over all of the blocks both in vertical and horizontal direction. Weighted sum of the vertical and horizontal edge differences are taken as the base of fitness function. The sum is squared to ensure that any major differences are weighted most heavily. Fitness is defined as being inversely proportional to this squared sum of differences between the ideal and candidate systems. The relationship depicted above allows us to establish a basis of comparison between the members in the population. Those members that have the largest square of summed differences are considered less fit. These members are assigned lower probabilities of crossover. Conversely, those with lower squares of summed difference values are assigned higher probabilities of crossover since they represent the fitter members. Probability of crossover is assigned to each member based on the relative fitness amongst one another. This normalizes the set of fitness grades. Normalization forces the fitness to grades between the values of zero and one, which are subsequently used as a set of crossover probabilities corresponding to member fitness. A random number is generated to determine which element will be selected for breeding. This random number falls within a particular range of crossover probability. This range corresponds to a particular coefficient set, which is subsequently chosen as a breeding member.

GA parameters: The genetic algorithm is designed to be able to optimize several d ifferent types of filters as well as to adapt and modify its population in different ways. To do this, GA incorporates a variety of different variables and parameters that can be altered depending on the application. The first parameter is the number of genetic iterations. This is an important variable as it determines how long the population breeds in an attempt to improve the fittest member. Generally it can be said that the higher the number of iterations had chosen, the fitter the members of the population become. A second and equally important input variable to this GA is the filter order. The filter

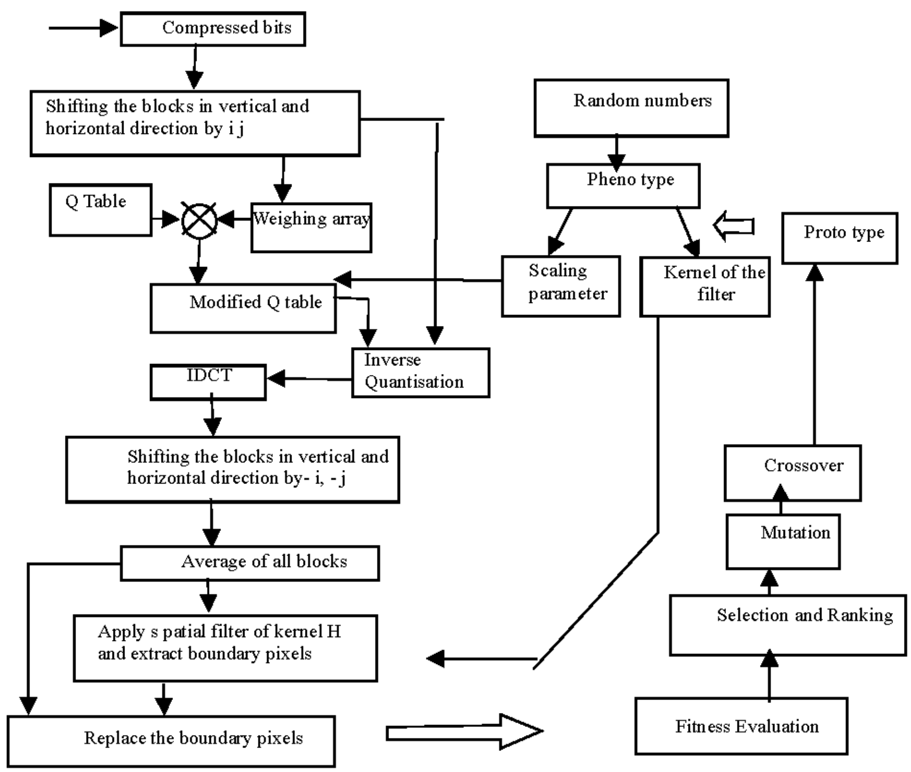

Fig. 3: Schematic diagram of boundary pixel replacement

order determines not only how many coefficients make up each member of the population, but also the filter's ability to approximate its ideal specified counterpart. Generally, it can be said that higher order filters are necessary in order to realize sharper responses. To accommodate for this factor, it is necessary to vary the filter order depending on the application. A variable exists to control the frequency of population mutation. A mutation probability is created to allow for random mutation at a probabilistic frequency. A higher mutation probability forces the population to mutate more frequently. Likewise, a lower mutation probability forces the population to mutate less frequently.

Fitness functions are opted with the fact that the fittest members contain characteristics that best match those of the ideal outcome. Different chromosomes are generated and the fitness values of the decoded images are generated. The population iterates the process of fitness evaluation, crossover, selection, breeding and mutation until the population is comprised of members representing the fittest value. At this point the population is said to be converged and produces the optimal result.

ARTIFACT REDUCTION WITH MODIFIED Q AND OPTIMAL BOUNDARY PIXEL REPLACEMENT

The schematic diagram of the efficient proposed algorithm is depicted in Fig. 3.

Modified quantisation table: Modified dequantization table is obtained by scaling the original quantization table, transmitted with the compressed image. New quantization table Q1 (i, j) is computed from the original quantization table Q(i, j) as

$$Q1\ (i,j) = \lambda^{(i+j)} * Q(i,j)\ . \tag{13}$$

Quantitative analysis of the conventional algorithm and the modified Q algorithm are tabulated with the parameters say SNR, MSE and TBE in Table 1 and 2 respectively.

Boundary pixel replacement approach: Previously discussed algorithms eliminate the artifacts to some extend only. In order to improve the performance, especially for blocking artifacts we can go for the

Table 1: JPEG: Filter+ Modified with 16 coefficients H=[1 1 10;1 1 1;10 1 1]Image :Cameraman

Size	Bpp	Cr	SNR	PSNR*10^4	H	MSE	TBE	Original bits	Comp	ENT	DET
32	1.051	0.1313	41.83	3.86	8192	89.62	53.92	8192	1076	0.58	1.522
40	1.045	0.1306	42.01	3.71	12800	89.22	67.11	12800	1672	0.7	2.17
64	0.9858	0.1232	42.01	3.69	327688	89.22	110.84	327688	4038	0.83	5.16
80	0.9816	0.1227	42.22	4.03	51200	88.74	100.24	51200	6282	1.43	7.2
128	0.9492	0.1187	42.32	3.91	131072	88.53	125.56	131072	15552	5.02	10.03
160	0.9410	0.1176	42.47	4.16	204800	88.19	143.22	204800	24090	11.14	33.71

Table 2: JPEG: Filter+ Modified with 16 coefficients H=[1 1 1;1 -8 1;1 1 1] Image :Cameraman

Size	Bpp	Cr	SNR	PSNR*10^4	H	MSE	TBE	Original bits	Comp	ENT	DET
32	1.051	0.1313	-7.92	1.664	8192	310.82	1.117	8192	1076	0.6	1.553
40	1.045	0.1306	-4.48	1.66	12800	285.25	1.114	12800	1672	0.41	2.413
64	0.9858	0.1232	1.71	1.67	327688	244.36	1.73	327688	4038	1.07	4.67
80	0.9816	0.1227	4.79	1.63	51200	226.19	1.86	51200	6282	1.58	7.28
128	0.9492	0.1187	10.22	1.64	131072	197.51	1.73	131072	15552	5.24	19.33
160	0.9410	0.1176	12.32	1.66	204800	187.41	2.32	204800	24090	9.67	33.34

Table 3: JPEG: Filter+ Modified with 16 coefficients H=[1 3 1;1 -8 1;1 2 1] Image :Cameraman

Size	Bpp	Cr	SNR	PSNR*10^4	H	MSE	TBE	Original bits	Comp	ENT	DET
32	1.051	0.1313	-376	1.36	8192	653.8	1.1.401	8192	1076	0.35	1.92
40	1.045	0.1306	-38.	9.69	12800	660.68	844.45	12800	1672	0.66	2.14
64	0.9858	0.1232	-38.1	1.095	327688	674.95	1310	327688	4038	0.94	4.68
80	0.9816	0.1227	-39.2	1.27	51200	679.54	1342	51200	6282	1.59	7.27
128	0.9492	0.1187	-39.5	1.1	131072	685.53	1274	131072	15552	5.23	20.1
160	0.9410	0.1176	-39.6	1.22	204800	687.57	1641	204800	24090	10.27	33.71

Table 4: JPEG: Filter+ Modifiedwith 16 coefficients H=[10 30 1; 11 12 1; 11 12 41] Image :Cameraman

Size	Bpp	Cr	SNR	PSNR*10^4	H	MSE	TBE	Original bits	Comp	ENT	DET
32	1.051	0.1313	-186.53	1.12	8192	2.71	6.35	8192	1076	0.35	1.74
40	1.045	0.1306	-186.91	1.42	12800	2.73	9.52	12800	1672	0.66	2.16
64	0.9858	0.1232	-187.57	1.15	327688	2.77	1.51	327688	4038	1.06	4.09
80	0.9816	0.1227	-187.83	1.14	51200	2.79	1.41	51200	6282	1.46	7.29
128	0.9492	0.1187	-188.12	1.31	131072	2.81	1.79	131072	15552	4.91	19.38
160	0.9410	0.1176	-188.21	1.37	204800	2.82	1.92	204800	24090	10.214	33.45

Table 5: JPEG: opt H +Boundary pixel Replaced(1) Image :Cameraman

Size	Bpp	Cr	SNR	PSNR*10^4	H	MSE	TBE	Original bits	Comp	ENT	DET
32	0.1289	0.0162	38.35	5.02	8192	97.77	226.74	8192	132	0.6	2.4
40	0.1288	0.0161	39.3	4.79	12800	95.47	287.71	12800	206	0.78	2.43
64	0.1279	0.016	40.24	4.33	327688	93.25	375.89	327688	524	1.87	2.81
80	0.1275	0.0159	40.34	5.06	51200	93.02	367.96	51200	816	2.1	3.18
128	0.1266	0.0158	40.87	5.04	131072	91.78	482.26	131072	2074	5.77	5.77
160	0.1265	0.0158	41.13	5.008	204800	91.19	540.63	204800	3240	10.83	10.35
256	0.1264	0.0158	41.58	5.18	524288	90.18	682.08	524288	8285	44.75	49.15

approach say boundary pixel replacement approach. Blocking artifacts are only due to boundary pixels. Hence the minimization of the blocking error in the $(i,j)^{th}$ block is carried out by using the intensity values of the neighboring pixels in the adjacent blocks say $(i, j - 1)^{th}$ block, $(i - 1, j)^{th}$ block, $(i, j + 1)^{th}$ block and $(i + 1, j)^{th}$ block boundary pixels. . In the proposed approach a spatial filter of dimension 3*3 is applied. Problem associated with this filtering is all the spatial regions are operated in the same manner. Due to this there come loss of information of required edges and some information of texture.

RESULTS

Experiments were conducted over various images. At the decoder, random generation of chromosomes decides the value of scaling parameter and the coefficients of the kernel. Here SNR is considered as the fitness function. Population of different sizes for different chromosomes is incorporated and the genes are tested for specific number of generation. Experimental results infer that convergence is effective when the number of chromosomes in the population and the number of generations are greater than or equal to eight. Authors analyzed the compression performance, looking for artifacts, error resilience and so on. . Results for the image cameraman for this algorithm is available in the subsequent tables. Proposed algorithm is implemented in MATLAB and the performances are evaluated quantitatively with four image quality metrics, SNR, PSNR, MSE and TBE. Performances are evaluated with filters of different kernels. Results are tabulated in Tables 1-4. From Tables, it is evident that SNR of the proposed algorithm is greater than the conventional one. Table 5-7 provides the performance of the proposed algorithm.

Table 6: JPEG: Opt H + boundary pixel replaced (4) Image: Cameraman

Size	Bpp	Cr	SNR	PSNR*10^4	H	MSE	TBE	Original bits	Comp	ENT	DET
32	0.3672	0.0459	39.95	4.214	8192	93.92	113.92	8192	132	0.86	2.1
40	0.3463	0.0433	40.39	4.46	12800	92.89	152.47	12800	206	2.35	4.11
64	0.3267	0.0408	40.89	3.94	327688	91.75	279.97	327688	524	2.29	2.78
80	0.3237	0.0405	41.23	4.38	51200	90.97	224.29	51200	816	3.44	3.04
128	0.3112	0.0389	41.59	4.25	131072	90.16	334.91	131072	2074	8.91	5.89
160	0.3096	0.0387	41.89	4.36	204800	89.47	367.71	204800	3240	15.32	10.28
256	0.3025	0.0378	42.24	4.52	524288	88.71	454.16	524288	8285	57.27	48.34

Table 7: JPEG: Opt H + boundary pixel replaced (16) Image: Cameraman

Size	Bpp	Cr	SNR	PSNR*10^4	H	MSE	TBE	Original bits	Comp	ENT	DET
32	1.051	0.1313	40.46	3.85	8192	92.74	97.04	8192	1076	1.49	2.08
40	1.045	0.1306	40.89	4.02	12800	91.74	128.98	12800	1672	2.42	2.15
64	0.9858	0.1232	41.39	359	327688	90.62	243.61	327688	4038	7.47	2.87
80	0.9816	0.1227	41.74	3.98	51200	89.82	205.45	51200	6282	15.32	3.14
128	0.9492	0.1187	42.02	3.67	131072	89.19	234.99	131072	15552	20.64	5.32
160	0.9410	0.1176	42.26	4.25	204800	88.69	300.87	204800	24090	35.00	9.78
256	0.9174	0.1147	42.56	4.021	524288	87.69	354.93	524288	60120	155.57	46.74

Fig. 4a: O/p image-conventional algorithm Fig. (4b) O/p image-modified Q alone

Similarly PSNR, MSE values are less than the conventional one. Also the visual Quality is checked with human eye and found that visual quality is better for our algorithm rather than the conventional one. Algorithm is tested with noisy images also and found to provide better performance (Fig. 4).

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