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Pillayar Thunai Kali Amman Thunai Sri Anjaneyar Thunai Genetic Algorithm Optimization for Reducing Artifacts in Association with High Dynamic Range Processing in Favor of Low Vision Viewers

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Abstract: Research in progress focuses the use of Genetic Algorithm (GA) and High dynamic Range image Processing (HDR) for the effective retrieval of the compressed images. The key issue for many emerging applications in the field of visual communications is the efficient compression of image data before transmission. There exists a tradeoff between compression ratio and image quality. High quality images at low bit rates can be reconstructed only by eliminating the compression artifacts. Blocking artifacts exploits the correlation between the intensity values of boundary pixels of two neighboring blocks. Specifically, it is based on the theoretical and empirical observations. Under mild assumptions, quantization of the coefficients of two neighboring blocks increases the expected value of the Mean Squared Difference of Slope (MSDS) or Mean Squared Error (MSE). Based on this, the new parameter TBE (Total Blocking effect) is computed from the compressed image using the edge differences. Minimization of TBE can be implemented in transform domain with a modified quantisation table and filter. Efficient suppression of artifacts is 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. Genetic algorithm is one of the emerging optimization techniques which in turn find its applications image enhancement, segmentation, fractal compression and so on. So far GA has not been used for the optimization of the artifacts at the receiver. Hence an attempt is made to optimize the kernel of the filter and the scaling parameter of the quantization with GA. A spatial domain algorithm can enhance further the quality of the image by preserving fine details. HDR processing used for this purpose divide the image into luminance and chrominance component. Process is carried out in the logarithmic domain. Proposed technique manipulates the gradient field of the luminance image by attenuating the magniudes of large gradients. Fine details are preserved by solving a Poisson equation on the modified gradient field. This novel algorithm does not affect the compressibility of the original image and is characterized by low computational complexity.

Key words: Blocking artifacts, genetic algorithm, high dynamic range processing, total blocking effect, log coding

INTRODUCTION

In many multimedia applications image compression is required to substantially reduce the amount of image data. The higher resolution of the image is, the larger its data volume is. The large data volume of a high-resolution image brings difficulties in dealing with it. For any particular data source, the compression performance of a lossy compression scheme may be described by its rate-distortion characteristic, representing the potential trade-of between bit rate and the distortion associated with the lossy representation. Quantisation of the transform coefficients introduces error in the image representation and a loss of signal information. At high compression ratios, this introduced error produces visually undesirable patterns known as compression artifacts that can dramatically lower the perceived quality of a particular image. These compression artifacts not only deteriorate the visual quality of images but also perturb image processing, pattern recognition, segmentation and machine vision algorithms like edge detection and motion estimation. This in turn says the important problem that arises frequently in visual communications and image processing is the need to enhance the resolution of a still image extracted from a compressed video sequence. Guaranteeing a certain level of quality after compression has become a prime concern for content providers, as the quality in the resulting content is the most important

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factor in the success of an application in the market place. This can be achieved only by eliminating the compression artifacts of the reconstructed image. Hence it is stated that finding an optimal solution for the detection and elimination of compression artifact in the compressed image is the present problem to be handled. During this process of optimization, the other problem to be considered is the preservation of fine details of the image.

Another main objective of this project is to assist the low vision viewers in the software side to carry the different activities of their day to day life in a comfortable manner. People with reduced visual acuity have difficulties in reading small prints, or in viewing the compressed images with blocking artifacts. Low vision viewers suffer due to visual artifacts of decompressed images

The research methodologies for reduction of compression artifacts have attracted much attention since 1990s. Research works spotlight the problem of reducing compression artifacts of the images in different domains. There are three general approaches to cope with the compression artifact removal problem. In the first approach, the blocking effect is dealt with at the encoding side using overlapping schemes. The second approach uses some post processing techniques at the decoding side. Later as a third, there are some approaches in the literature, which have tackled the problem of compression artifact reduction completely in the transform domain. Problem has been solved already by some post processing and pre processing approaches. Still Ga is not at all used. This final approach is applied entirely in the compressed domain. This is in contrast to the large majority of the deblocking algorithms, which are applied in the spatial domain.

Chang and Kang presented (2005), a fast and systematic scheme is proposed 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 by using the predictors, which are constructed based on a broken line regression model (Lee *et al*., 2005). Averbuch and Zheludey designed (2004) a new family of biorthogonal wavelet transforms and describe their applications to still image compression. The transforms use finite impulse response and infinite impulse response filters that are implemented in a fast lifting mode. Proposed scheme in (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 thus improving over classic wavelet schemes. Based on the recently published Lookup Table (LUT) technique, this paper (Chung and Wu, 2005) presents a novel edge-based LUT method for inverse half toning which improves the quality of the reconstructed gray image

In this Study, the modeling is limited to "pixel classification," the relationship between wavelet pixels in significance coding. Similarly, the ordering is limited to "pixel sorting," the coding order of wavelet pixels (Peng and Kieffer, 2004). Gunturk *et al*. (2004) proposed a stochastic framework where quantization information as well as other statistical information about additive noise and image prior can be utilized effectively. Chen (2004) analyze the general context quantization problem in detail and show that context quantization is similar to a common vector quantization problem. When combining the contexts, the mutual information between the contexts and the encoded data will decrease unless the conditional probability distributions of the combined contexts are the same (Lu and Karan, 2005). This study presents (Chandler and Hemami, 2005) a contrast-based quantization strategy for use in lossy wavelet image compression that attempts to preserve visual quality at any bit rate.

A technique for block-loss restoration in block-based image and video coding, dubbed Recovery of Image Blocks Using the Method of Alternating Projections (RIBMAP), is developed (Park *et al*., 2004). The algorithm is based on orthogonal projections onto constraint sets in a Hilbert space. This method, (Huang and Salama, 2005) which is based on 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. The problem of recovering a high-resolution image from a sequence of low-resolution DCT-based compressed observations is considered by Park *et al*. (2004). The DCT quantization noise is analyzed and a model in the spatial domain is proposed as a colored Gaussian process (Gomez *et al*., 2005). In order to prevent ghosting effect occurrences, the weights of pixels, which belong to non monotone areas, are modified by dividing each pixel's weight by a predefined factor called a grade. This scheme is referred to as Weight Adaptation by Grading (WABG) (Averbuch *et al*., 2005).

Pre/post-filtering can be attached to a DCT-based block coding system to improve coding efficiency as well as to mitigate blocking artifacts (Tu *et al*., 2006). Previously designed pre/post-filters are optimized to maximize coding efficiency solely. Segall *et al*. (2004)

utilized the Bayesian framework to incorporate this information and fuse the super-resolution and post-processing problems. A tractable solution is defined and relationships between algorithm parameters and information in the compressed bit stream are established. This research describes the application of a Genetic Algorithm to production simulation (Robert and Sieffried, 1997). The simulation is treated as a detailed, stochastic, multi-modal function that describes a performance statistic. Based on Genetic Algorithms (GAs), the software searches for the appropriate procedures (Kazunors *et al*., 1998), such as filtering operations and their parameters and can segment target components in digital images, compared to rough objective images given by users. A coefficient dependent method for choosing thresholds is also briefly presented by Averkamby and Haudri (2003).

Unlike previous works, a maximum-likelihood approach is presented to the ringing artifact removal problem. This approach employs a parameter-estimation method based on the k -means algorithm (Seungjoon *et al*., 2001) with the number of clusters determined by a cluster-separation measure. Gunturk 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. One of these methods uses quantization-bound information (Gunturk *et al*., 2002) to define convex sets and then employs a technique called “Projections Onto Convex Sets” (POCS) to estimate the original image. Another uses a Discrete Cosine Transformation (DCT)-domain Bayesian estimator to enhance resolution in the presence of both quantization and additive noise paper (Gunturk *et al*., 2004). Multi frame constraint sets can be used to reduce blocking artifacts in an alternating-projections scheme (Gunturk *et al*., 2002). By combining an adaptive binary arithmetic coding technique with context modeling, a high degree of adaptation and redundancy reduction (Detlev *et al*., 2003) is achieved.

Authors 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 (Chengjie and Tac, 2002). A novel frequency-domain technique for image blocking artifact detection and reduction is presented in this research. For each block affected by blocking artifacts, its dc and ac coefficients are recalculated for artifact reduction (George, 2002). The advantages of the psycho physically motivated algorithm are used and the compression ratio remains unaffected (Jinshan *et al*., 2003). The previous contrast domain concept extended with inter and intra Quantisation (Fullerton and Peli, 2005) for moving images in this approach. The goal is to reduce memory requirements while increasing speed by avoiding decompression and space domain operations (Ricardo, 1998). Techniques are presented for scaling, previewing, rotating, mirroring etc

The smoothness constraint set is obtained (Alan *et al*., 2005), by an explicit modeling of smooth regions in the image using a spatially adaptive thin-plate splines. Based on the observation that blocking artifact along edge direction is difficult for human perception, a number of existing techniques have proposed to filter the edge pixels with low weight or bypass them altogether to avoid blurring (Gan *et al*., 2003). By considering the behavior of intensity evolution along and across edges, a new POCS-based algorithm using a new smoothness constraint set is proposed by Xiangchao Gan *et al*. (2003). This technique excludes pixels around the block edges from transmission. Rows and columns between the blocks are cancelled (Panis *et al*., 1997). These lines are reconstructed by sub sampling and over sampling filters at the block edges in the decoder. A new method for fractal image compression is proposed using Genetic Algorithm (GA) with elitist model. The technique described here utilizes the GA, (Suman *et al*., 1998) which greatly decreases the search space for finding the self similarities in the given image.For images compressed using the JPEG standard, image sharpening is achieved by suitably scaling each element of the encoding quantization table to enhance the high-frequency characteristics of the image (Konstantinos *et al*., 1999).

A model-based edge- reconstruction algorithm (Fan and Chan, 2000) for recovering the lossy edges in coded images is proposed. A model-based edge approximation and Gaussian smoothing, are used to reconstruct distorted edges. The development of The Quantization Table using Genetic Algorithms (Costa and Veiga, 2005), with the JPEG standard is a important method to create a better Quantization Table for each class of images and different sizes by the natural selection. Authors present a voting strategy to determine a set of morphological filters to be used for reducing the ringing artifacts. The set of selected filters is conveyed (Yen *et al*., 2005), to the decoder in the form of side information. Specifically, the adopted (eight) morphological filters are generated through the use of four predefined Structuring Elements (SEs) in conjunction with two morphological operations, namely, dilation and erosion. Next algorithm is based on an adapted total variation minimization approach constrained by the knowledge of the input intervals the unquantized cosine coefficients belong to. Although the proposed sub gradient method is converging in infinite time, experiments show that best results are obtained with a very few number of iterations (Francois et al., 2005). Sangkeun *et al.* (2006) and others developed a simple and efficient algorithm for dynamic range compression and contrast enhancement of digital images in the compressed domain..

Yaakov tsaig research paper (Tsaig *et al.*, 2005), explores the use of optimal decimation and interpolation filters in this coding scheme. It has been shown that the problem of finding optimal filters for a general, unknown, "black-box" coder can be written as a separable least squares problem in two sets of variables and elegantly this optimization problem is solved using the variable Projection method (Triantafyllidis *et al.*, 2002). An alternative method first reconstructs the DCT coefficients based on their observed probability distribution. Minami and Zakhor (1995) presented a new approach by to minimizing a new criterion called Mean Squared Difference of Slope (MSDS), while imposing linear constraints corresponding to Quantisation bounds. Algorithm devised by Aria Nosratinia, counter intuitively employs further compression to achieve image enhancement, which is not widely known or not entirely new (Aria, 2002). FengGao addresses the problem of reducing blocking effects in Transform coding using gradient flow with multiple constraints (2004). Blocking artifacts are detected with boundary pixels and optimization in filter design is achieved with greedy method .

The algorithm proposed by Ramamurthi 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 (Ramamurthi and Gershoin, 1986) accordingly to reduce blocking effects. An alternative novel method simply re-applies JPEG to the shifted versions of the already-compressed image and forms an average (Aria, 2001). This approach, despite its simplicity, offers better performance than other known raging. Algorithm consists of edge adaptive diffusion process before DCT –JPEG compression (Ivan and Tomas, 2005). Preprocessing helps in preserving the true contours. .Selecting an appropriate quantization table for Joint Photographic Exploitation Group (JPEG) data compression of a class of images can be an arduous task. 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 (Berman *et al.*, 1993). A discussion on compression artifacts, survey of several algorithms that reduce compression artifacts and the current bottleneck and future are done in this work (Shen and Kuo, 1997).

Jim Chou and other authors introduce a fast, easy-to-implement algorithm that removes blockiness by performing a simple nonlinear smoothing of pixels (Jim *et al.*, 1998). Noise model is considered in a systematic way (Sziranyi *et al.*, 1998). Relying on the theory of an isotropic diffusion filtering, we claim that it is possible to achieve artifact reduction, while preserving the main structure of the image. A group of artifact-reduction methods are statistical estimation methods (Stevenson, 1993). Xiong uses an over complete wavelet representation to reduce the quantization effects of block-based DCT (Xiong *et al.*, 1997). In the POCS-based method, closed convex constraint sets are first defined that represents all of the available data on the original un coded image (Yang and Galatsanos, 1997). The success of set-theoretic methods depends highly on the constraint sets, whose intersection gives the feasibility set: the set of all acceptable solutions (Combettes, 1993). Gopinath *et al.* (1994) proposed an enhancement method involving the over sampled wavelet transform, in conjunction with a soft threshold motivated by the mini max arguments.

Implementation architecture: Implementation architecture is divided into seven main steps as specified below.

JPEG CODER AND DECODER

A source image represented in the RGB color space is converted into an image represented in the YCbCr color space in encoding processes. Data reduction of chrominance components Cb and Cr is performed in JPEG/JPEG 2000 compression as required. Most of pieces compression software adopt the 4:1:1 sampling as the default setting. The source image is transformed into the spatial frequency domain by DCT in JPEG compression respectively. DCT-coefficient data are quantized in JPEG compression by a quantisation table. The quantisation process used in this step controls the compression level of an image. The quantisation stage is a lossy process

Arithmetic entropy encoding is performed to further educe compressed image data volume Huffman coding is a commonly used method Fig. 1. Arithmetic entropy decoding is performed at the receiver. The compressed image data in the spatial frequency domain is transformed into the image domain by inverse DCT in decompression. Using the same quantisation concept, the inverse algorithm performs dequantization. Inversely, the transformation from the YCbCr color space to the RGB color space is executed in the decoding process. Input and output images of the conventional method is projected as Fig. 2 and 3.

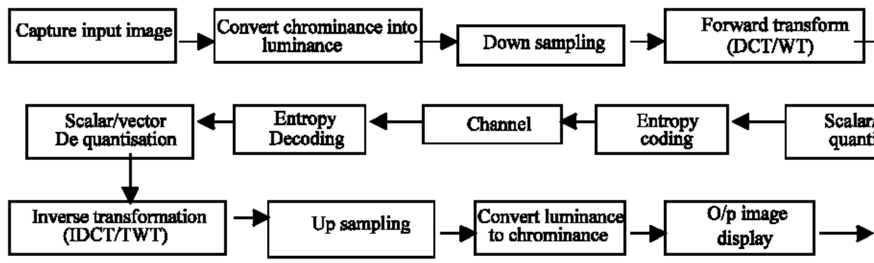

Fig. 1: Conventional JPEG coder and decoder

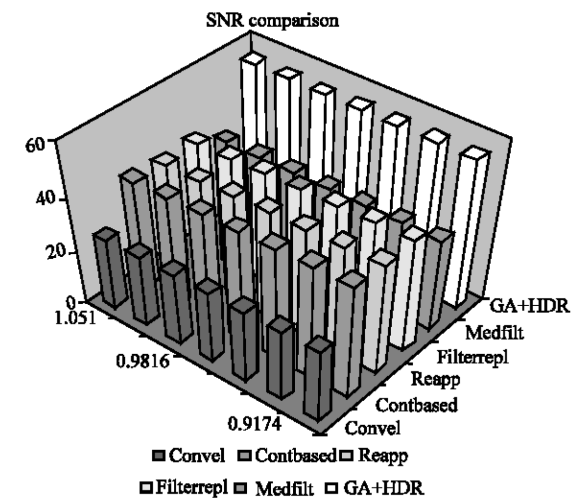

Fig. 2: SNR comparison

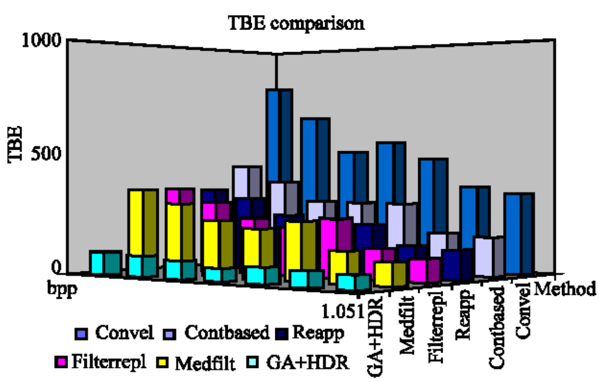

Fig. 3: TBE comparison

DECODING WITH THE MODIFIED QUANTISATION TABLE AND CYCLIC SHIFTING

The coefficients in the output DCT block are arranged left to right and top to bottom in order of increasing spatial frequencies in the horizontal and vertical spatial dimensions, respectively. The spatial frequency properties of the DCT coefficients provide a natural way to define a contrast measure in the DCT domain. The 64 coefficients of each block is classified into 15 different frequency bands. A band consists of approximately equal radial frequencies. As the band number increases, the frequency content of the bandpass image block corresponds with higher frequencies and, thus, creates a primitive multiscale structure. First coefficient d_{00} represents the DC level of the block and the other coefficients represent spatial frequencies that increase with their distance from the origin. For instance, coefficients $d_{(4,4)}$ represents a spatial frequency of 4 cycles/block in the horizontal and vertical directions, respectively. Similarly coefficient $d_{(1,3)}$ also represents the spatial frequency of 4 cycles/block in the horizontal and vertical directions. Now all the coefficients associated with the spatial frequency of 4 cycles/block can be combined which in turn form the 4th sub-band. In this manner, 64 coefficients, can be revealed totally to form 14 frequency bands. A band limited contrast measure in the DCT can be given as

$$C_n = \frac{E_n}{E_n - 1} \quad (1 \le n \le 14, n \in Z)$$

where E_n represents the Energy of n^{th} band and C_n represents the corresponding contrast. E_n can be computed as

$$E_n = \frac{\sum_{\forall i+j=n} \left| d_{i+j} \right|}{N_n}$$

The numbers of sub bands in each domain are mathematically defined as

$$N_n = \begin{cases} n+1, & n < 8 \\ 14 - n + 1, & n \ge 8, \text{ where n ranges from 0 to14} \end{cases}$$

Modified dequantization table is obtained by weighting the quantisation table, transmitted with the compressed image, as derived below. Now the enhanced DCT coefficients are computed as

$$d_{(i,j)} = \lambda^{(i+j)} d(i,j)\text{, where}$$

$d_{(i,j)}$ = Original coefficients, $d_{(i,j)}$ = modified coefficients. The above processing can be realized by weighing the quantisation table Q as

$$Q(i,j) = \lambda^{(i+j)} Q(i,j), \text{ where}$$

Q(i,j) = Original quantisation table; Q(i,j) = modified Quantisation table and λ = Scaling parameter.

Shifting and averaging: This algorithm shifts the recovered image for a specific number of times. Then it applies DCT, quantisation, inverse quantisation and inverse DCT sequentially to all the shifted images. The whole information is then averaged. Summarized procedure is given as

- Shift the compressed images in vertical and horizontal directions by (i; j).
- Apply JPEG to shifted image.
- Shift the result back, i.e. vertically and horizontally by (i,j).
- Repeat for all possible shifts in the range [n1 ,n2] and [m1, m2] in the horizontal and vertical direction respectively
- Average all images

DETECTION OF COMPRESSION ARTIFACTS AND COMPUTATION OF EDGE DIFFERENCE VECTORS

Model of blocking artifact: Consider two adjacent 8*8 blocks b1 and b2 , with average values $\mu1$ and $\mu2$, respectively, where $\mu1 \neq \mu2$. Let ε_i and δ_i represents noise model of these two blocks b1 and b2. Then mathematically these two blocks can be written as

$$b1 = \mu1 + \varepsilon_1 + \delta_1 \; ; \; b2 = \mu2 + \varepsilon_2 + \delta_2$$

When the corresponding DCT blocks of b1 and b2 are quantized using a large quantization parameter, most of the DCT coefficients become zero, which reduces the effect of the variance of $\varepsilon_{i,j}$ and $\delta_{i,j}$. As a result, a 2-D step function between b1 and b2 (due to ¹1 6= ¹2) may become visible, creating a blocking artifact. Based on this observation, one can now form a new shifted block b(n) composed of the right half of b1 and the left half of b2 which in turn is to be used for the blocking artifact analysis. This blocking artifact between blocks b1 and b2 can be modeled as a 2-D step function. This step function of the new block can be mathematically expressed as

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

The larger the value of the more serious the locking effect is taken to be, provided that the background brightness and local activity remain unchanged.

Mathematical description of blocking effect detection: After the BDCT transform, a decoded $N \times N$ image X with blocking effects can be expressed in a sub matrix form as

$$X = \begin{pmatrix} x_{1,1} \; x_{1,2}........x_{1,n} \\ x_{2,1} \; x_{2,2}........x_{2,n} \\ .... \\ x_{n,1} \; x_{n,2}........x_{n,n} \end{pmatrix}$$

where Xi,j is a $B \times B$ sub matrix, i, j = 1, 2, . . . , n and n = N/B is an integer. Every Xi,j is called a block. There exist blocking artifacts between every adjacent block boundaries. Obtain the first and the last column of each sub matrix. Then the difference vector of the last column of the nth block and the first column if the n+1th block is a measure of the blocking effects in the column direction of X. Define the column edge difference vector V_c which in turn consists of all the column differences in between different blocks. Mathematically this can be expressed as

$$V_c = \{ V_c^1, V_c^2, V_c^3, \ldots\ldots\ldots V_c^n, \},$$

where

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

where $X_{i,j}(:,k)$ = kth column of $X_{i,j}$ submatrix.

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

$$V_r = \{ V_r^1, V_r^2, V_r^3, \ldots\ldots\ldots V_r^n, \},$$

where

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

$X_{i,j}(k,:)$ = k^{th} row of $X_{i,j}$ submatrix.

Norm of V_r gives a measure about the blocking effects in the row direction. Now the total blocking edge value is computed from the norm of row and column edge difference vector. Let us say the parameter as Total Blocking Error (TBE). Hence

$$TBE = \text{norm of } V_r + \text{norm of } V_c = \alpha_1 \|V_c\| + \alpha_2 \|V_r\|$$

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 reduces TBE

MANIPULATE THE QUANTIZED COEFFICIENTS WITH THE OPTIMIZED FILTER AND THE SCALING PARAMETER

Based on the fact that, only the pixel values on the block boundaries need to be smoothed, an optimal filter design method is to be designed on a constraint manifold. The constraint manifold can be regarded as a lower dimensional manifold imbedded into multi dimensional linear space RN2 . So our research can be converted into an optimization problem on the constraint manifold. This problem can be solved by using the existing gradient flow method on the manifold. Here, we propose the optimization of the filter H with Genetic Algorithm (GA) such that, when the image vector f of X passes through the filter H, the corresponding edge differences and so TBE can be minimized or kept to three given real parameters ε_1 and ε_2 and ε_3 respectively.Mathematically it is written as

$$\|V_c\| = \varepsilon_1 \; \|V_r\| = \varepsilon_2 \text{ and } TEB = \varepsilon_3$$

The above equation constitutes a lower manifold in the linear space, which we call the constraint manifold. Therefore, the problem of reducing blocking effects is converted into the optimization problem as: Design an optimal filter H on the constraint manifold.

GA optimization: For the correct feature extraction, segmentation 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 can be given as m*n. Trying all cases to find out the best one practically impossible when there are lots of filters available. An optimization approach is therefore needed to search filters of the proper type and order. In this paper, a genetic algorithm is used to search filters of the proper type with fixed 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. Coefficients of kernel used for filtering and the scaling parameter of the modified quantisation table are to be optimized. Objective function is the evaluation of edge difference vectors. SNR and TBE are the fitness function utilized for the scaling parameter and the coefficients of the filtering kernel respectively. Filters may be Low pass filters of IIR or FIR. The input image is smoothed by the filter and impulse noise spikes of the image are removed by the median filter. In addition scaling parameter is also optimized.

IMAGE QUALITY

There is a wealth of research on subjective and/or objective image quality measures to reliably predict either perceived quality across different scenes and distortion types or to predict algorithmic performance computer vision tasks. The measures are categorized into pixel difference-based, correlation-based, edge-based, spectral-based, context-based and HVS-based (Human Visual System-based) measures. Image quality measures are figures of merit used for the evaluation of imaging systems or of coding/processing techniques. The current work takes into account four quality metrics to compare the proposed algorithm with the existing algorithms. They are SNR, PSNR, MSE, TBE.

PROCESS THE IMAGE WITH HDR IN GRADIENT DOMAIN

This system relies on the widely accepted assumptions that the human visual system is not very sensitive to absolute luminance's reaching the retina, but rather responds to local intensity ratio changes and reduces the effect of large global differences, which may be associated with illumination differences. This algorithm is based on observation that any drastic change in the luminance across a high dynamic range image must give rise to large magnitude luminance gradients at some scale. Fine details, such as texture, on the other hand, correspond to gradients of much smaller magnitude. Solution is to propagate the desired attenuation from the level it was detected to the full resolution image. Thus, all gradient manipulations occur at a single resolution level and no halo artifacts arise. Most of the high dynamic range compression algorithms operate in the logarithmic domain; Determine the reduced vector field, G, for the low dynamic range image. Next solve the Poisson equation, say Lap (I) = div (G), to get an appropriate image. The scientific principle of this type of technique is based on the image formation model: I(x, y) = L(x, y)*R(x, y), which states that image intensity function I(x, y) is the product of the illuminant function L(x, y) and the scene reflectance function R(x, y). Since, the reflectance value can't be changed, change are to be made with the luminance value. So, the resultant will be

$$\bar{I}(x, y) = R(m, n) * \dot{L}(x, y)$$

Obtain the logarithm of the intensity of the image as

$$H(x, y) = \log (L(x, y))$$

Goal is to compress large magnitude changes in H, while preserving local changes of small magnitude, as much as possible. It is achieved by applying an appropriate spatially variant attenuating mapping function Ø to the magnitudes of the derivatives H(x, y) . as

$$H'(x, y) = \text{gradient}(H(x, y));$$

More specifically, this can be computed the average of the gradient values in both x and y direction. The attenuated derivative is obtaine

$$G(x, y) = H(x, y) * Ø(x, y)$$

where $\Phi(x, y)$ is the attenuation factor, which in turn can be varied. The modified image is found by integrating the gradient field. Reduced dynamic range signal can be obtained by integrating the compressed derivatives. For a two dimensional signal the integration achieved with a poison equation. Original image can be reconstructed with the exponent component of the integrated image

$$I(x,y) = C + \int G(x,y)\, dx\, dy$$

Since, we can't integrate the two dimensional image, the above one can be solved using Poisson equation as.

$$I\,new = \text{div}\, G$$

The details are then added to the range compressed low frequency information to reconstruct a visually accurate low dynamic range version of the image.

RESULTS AND DISCUSSION

Different images were tested randomly and each image was compressed in JPEG domain. The decompressed images and the uncompressed original images were compared and the performance is measured in terms of SNR, PSNR, MSE and TBE. Algorithm is implemented both for Monochrome (cameraman) as well as color images (flowers) and the results are projected for the monochrome image. Scaling parameter can take any integer value but, it was found results are of much distorted above 1.4. Modified algorithm produces better results in the range 0.75 to 0.9. Table 1 compares the performance of SNR of different existing algorithm with the proposed algorithm for the monochrome image "cameraman". Table 2 provides the comparison of the blocking artifact TBE of different existing algorithm with the proposed algorithm for the monochrome image. Figure 4 to 10, shows the changes in the visual quality of the

Table 1: SNR Comparison

						SNR					
Size	bpp	Cr	Total	Comp	H	Convel	ModQ	Shif	Filterrepl	Medfilt	hdr
32	1.051	0.1313	8192	1076	8192	26.61	40.61	39.61	40.46	34.64	55.96
40	1.045	0.1306	12800	1672	12800	26.80	40.98	40.05	40.89	34.59	55.91
64	0.9858	0.1232	327688	4038	327688	26.95	41.46	40.61	41.39	34.84	55.63
80	0.9816	0.1227	51200	6282	51200	27.07	41.79	40.92	41.74	34.62	55.92
128	0.9492	0.1187	131072	15552	131072	27.18	42.07	41.23	42.02	34.56	55.86
160	0.9410	0.1176	204800	24090	204800	27.28	42.297	41.5	42.26	34.604	55.7

Image :Cameraman

Table 2: TBE Comparison

						TBE					
Size	bpp	Cr	Total	Comp	H	Convel	ModQ	Shif	Filterrepl	Medfilt	hdr
32	1.051	0.1313	8192	1076	8192	340.91	165.59	121.4	97.04	96.04	62.3
40	1.045	0.1306	12800	1672	12800	371.29	176.46	132.26	128.98	128.68	65.2
64	0.9858	0.1232	327688	4038	327688	486.71	294.02	212.41	243.61	242.32	67.39
80	0.9816	0.1227	51200	6282	51200	567.75	296.68	190.97	205.45	205.45	54.43
128	0.9492	0.1187	131072	15552	131072	524.74	299.6	242.07	234.99	233.45	73.10
160	0.9410	0.1176	204800	24090	204800	678.85	387.97	310.31	300.87	310.87	85.23

Image :Cameraman

4.1 o/p image bpp-3.2197 SNR = 27-46 | 4.2 o/p image bpp-0.9492 SNR = 27-18 | 4.3 o/p image bpp-0.3112 SNR = 26.76 | 4.4 o/p image bpp-0.1266 SNR = 26.28

Fig. 4: Input and output images of conventional quantisation table

5.1 o/p image bpp-3.2197 SNR = 27-47 | 5.2 o/p image bpp-0.9492 SNR = 27-187 | 5.3 o/p image bpp-0.3112 SNR = 26.82 | 5.4 o/p image bpp-0.1266 SNR = 26.32 (ord,med)

Fig. 5: Input and output images of conventional quantisation table with median filter

6.1 o/p image bpp-.2197 SNR = 34.2 | 6.2 o/p image bpp-.9492 SNR = 34.15 | 6.3 o/p image bpp-.3112 SNR = 33.81 | 6.4 o/p image bpp-0.1266 SNR = 33.27

Fig. 6: Output images of shifting with conventional quantisation

7.1 o/p image bpp-3.2197 SNR = 40.4 | 7.2 o/p image bpp-0.9492 SNR = 40.36 | 7.3 o/p image bpp-0.3112 SNR = 39.39 | 7.4 o/p image bpp-0.1266 SNR = 39.59

Fig. 7: Output images of shifting with modified quantisation in one stage

8.1 o/p image bpp-3.2197 SNR = 42.1 | 8.2 o/p image bpp-0.9492 SNR = 41.99 | 8.3 o/p image bpp-0.3112 SNR = 41.58 | 8.4 o/p image bpp-0.1266 SNR = 40.87 (mod,med)

Fig. 8: Output images of modified quantisation and median filter

9.1 o/p image bpp-3.2197 SNR = 42.1 | 9.2 o/p image bpp-.9492 SNR = 42.1 | 9.3 o/p image bpp-.3112 SNR = 41.57 | 9.4 o/p image bpp-.1266 SNR = 40.8

Fig. 9: Output images with modified quantisation table

10.1 o/p image bpp-3.2197 SNR = 55.961 | 10.2 o/p image bpp-0.9492 SNR = 55.59 | 10.3 o/p image bpp-0.3112 SNR = 55.92 | 10.4 o/p image bpp-0.1266 SNR = 55.93 (hdr)

Fig. 10: Outputimages with modified quantisation table and HDR

image with different existing algorithm. Figure 9 bestows that the proposed algorithm has improved the signal to noise ratio and minimized The Blocking Effect (TBE). Corresponding graphical representation is available in Fig. 2 and 3.

Application: One of the main objectives of this project is to assist the low vision viewers in the software side to carry the different activities of their day to day life in a comfortable manner. It describes the capacity of the visual system to resolve detail. Visual acuity -x/y is defined as to resolve letters from a distance of x units, by a person to resolve from a distance of y units. People with reduced visual acuity have difficulties in reading small prints, or in viewing the compressed images with blocking artifacts. Millions of people are visually impaired. The number of disabling visual problems increases with the growing aging population. Visually impaired people have difficulties in reading small print, watching television, recognizing faces, etc. Much research and rehabilitation effort has been aimed at improving the reading ability of low-vision patients. Proposed scheme concentrates in removing the undesirable features of the compressed image in the JPEG domain itself. Later it can be extended to MPEG domain.

CONCLUSION

This new embedded image coding algorithm in JPEG/JPEG 2000 domain for the removal of artifacts with HDR enhancement as a post processing scheme was implemented in Matlab. Several images were tested and fruitful results were obtained both for monochrome and color image. Quantitative and qualitative measures at each and every stage have been compared with the already existing Techniques. Our experimental results show that the proposed method of measuring blocking artifacts is effective and stable across a wide variety of images. Moreover, the proposed blocking artifact reduction method exhibits satisfactory performance as compared to other post-processing techniques. The proposed technique has low computational cost hence can be used for real-time image/video quality monitoring and control, especially in applications where it is desired that the image/video data be processed directly in the DCT-domain.

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