Classification-Based Adaptive Regularization for Fast Deblocking

*Tae Keun Kim, **Sang Kwang Lee, *Joon Ki Paik and **Yo Sung Ho
*Department of Electronic Engineering, Chung-Ang University
221 Huksuk-Dong, Tongjak-Ku, Seoul 156-756, Korea
**Department of Information and Communications,
Kwangju Institute of Science and Technology (K-JIST)
572 Ssangam-Dong Kwangsa-Ku Kwangju, 506-712, Korea

ABSTRACT

In this paper we propose an iterative image restoration method using block edge classification for reducing block artifact in compressed images. In order to efficiently reduce block artifacts, a block is classified as edge or non-edge block, and the adaptive regularized iterative restoration method is used.

The proposed restoration method is based on the observation that the quantization operation in a series of coding propocess is a nonlinear and many-to-one mapping operator. And then we propose an adaptive iterative image restoration algorithm for removing the nonlinear and space-varying degradation. With some minor modifications the proposed image restoration method can be used for postprocessing reconstructed image sequences in HDTV, DVD, or video conferencing systems.

Keywords: Image degradation model, Deblocking filter, Adaptive iterative restoration

1. INTRODUCTION

As the demand for video communication has grown, various efficient image compression methods have been developed and standardized. Especially, high quality image communication with low bit-rate is gaining growing interests in applications to video conferencing, videophone, interactive TV, etc.

The block discrete cosine transform (BDCT) is the most widely used technique for the compression of both still and moving images. The main drawback of the BDCT based compression techniques is the block artifact which represents the artificial discontinuity between adjacent blocks, and results from the independent processing of the blocks without taking into account the between-block pixel correlations.[1]

To reduce block artifact without increasing the bit rate, the following approaches have been proposed, such as; (i) lowpass filtering on the boundary region between blocks,[2] (ii) regularized image restoration methods based on the theory of projections onto convex sets (POCS) or constrained least squares (CLS),[1] (iii) prediction of AC coefficients using the mean squared difference of slope (MSDS) between the neighboring pixels on their boundaries,[4] and (iv) optimization based on boundary orthonormal function method[5].[6] The lowpass filtering approach has the advantage that it does not require any additional information to be transmitted or any additional operation. But this approach results in unnecessary image blurring. The method based on POCS or CLS needs increasing amount of processing time due to iterative procedure. So it is not suitable for real-time video processing. AC prediction method has the disadvantage of high computation complexity for optimization process, and boundary orthonormal function based optimization method may result in different type of distortion at the cost of reducing block artifacts.

In order to remove block artifacts more efficiently in BDCT-based compressed images, we propose an adaptive iterative image restoration method.

Further author information-
J. K. P. : Phone:+82-2-820-5300, Fax:+82-2-825-1584, E-Mail:paikj@chungang.edu
Y. S. H. : Phone:+82-62-970-2211, Fax: +82-62-970-2204, Email: hoyo@kjist.ac.kr

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2. DEGRADATION MODEL FOR BLOCK ARTIFACT

In order to simplify derivation of the proposed algorithm, we use the following, one-dimensional vector representation of an $N \times N$ image $x(m,n)$ for $B \times B$ block-based processing.

$$x = [x_1^T, x_2^T, \cdots, x^T_{\frac{N^2}{B^2}}]^T, \tag{1}$$

where x_k for $k = (p-1) \cdot (N/B) + q$ represents the lexicographically ordered B^2 elements in the (p,q)-th block.

The degradation model of a BDCT-based compression-reconstruction process can be written as

$$y = C^{-1} D^{-1} Q C x, \tag{2}$$

where y represents the reconstructed image with block artifacts due to the quantization of BDCT coefficients, C and C^{-1} respectively the block-based forward and inverse DCT matrices, and Q and D^{-1} respectively the corresponding quantization and the inverse quantization matrices. The corresponding block diagram is shown as the degradation phase in Fig. 1. In the figure, the restoration phase represents the post-filtering process for reducing block artifacts.

Based on the image representation model given in (2), the above mentioned matrices can be represented as

$$C = \begin{bmatrix} [c] & 0 & \cdots & 0 \\ 0 & [c] & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & [c] \end{bmatrix}, \tag{3}$$

$$\text{and} \quad C^{-1} = \begin{bmatrix} [c]^{-1} & 0 & \cdots & 0 \\ 0 & [c]^{-1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & [c]^{-1} \end{bmatrix},$$

where $[c]$ and $[c]^{-1}$ repectively represent the forward and the inverse DCT matrices, with size $B^2 \times B^2$, for processing lexicographically ordered $B \times B$ image blocks. And the quantization operator, denoted by Q in (2), is further divided into two successive operations, division and rounding, such as

$$Q = RD. \tag{4}$$

In (4), the division matrix D can be represented as

$$D = \begin{bmatrix} [d_1] & 0 & \cdots & 0 \\ 0 & [d_2] & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & [d_{\frac{N^2}{B^2}}] \end{bmatrix}, \tag{5}$$

where the k-th diagonal submatrix $[d_k]$ is a diagonal matrix, whose diagonal elements are determined by the following way. For example, if we use a JPEG-based quantization table,[3] diagonal elements of $[d_k]$ can be represented as

$$d_k(l,l) = \frac{1}{t(i,j)}, \tag{6}$$

for $l = (i-1) \cdot 8 + j$ and $1 \le i, j \le 8$, where $t(i,j)$ represents the (i,j)-th value in the quantization table shown in Fig. 2.

The rounding operation, denoted by R in (4), is a nonlinear and many-to-one mapping operator in the entire degradation process, or equivalently in the compression-reconstruction process. And it can be written as a diagonal matrix whose diagonal elements performs rounding operation to the corresponding element of the input vector. The inverse quantization matrix, denoted by D^{-1}, simply represents the inverse of the division matrix D.

3. PROPOSED ITERATIVE DEBLOCKING METHOD

In this section we formulate the proposed iterative image restoration based on the degradation model described in the previous section. In subsetion 3.1, we derive the proposed restoratin algorithm, and in subsection 3.2, an edge classification algorithm using DCT coefficients is proposed.

3.1. Spatially adaptive image restoration

Let $H = C^{-1}D^{-1}QC$, then we can rewrite (2) as

$$y = Hx, \tag{7}$$

where H can be considered as an image degradation operator. If we assume that the degradation process is linear and space-invariant, or equivalently that the matrix H has constant elements and block-circulant structure, * then we can easily find the soulution by using the linear minimum mean square error (LMMSE) or constrained least squared error (CLS) type filters in the discrete Fourier transform (DFT) domain.[7] On the other hand, if the degradation process is linear and space-variant, or equivalently H has constant elements and does not have the block circulant structrure, spatially adaptive iterative type image restoration techniques can estimate the original image with a sufficient number of iterations.[8]

By this reason we propose an adaptive iterative image restoration algorithm for removing the nonlinear and many-to-one mapping operator. A general image restoration process based on the constrained optimization approach is to find x which safisfies

$$||y - H\hat{x}||^2 = 0 \tag{8}$$

subject to

$$||A\hat{x}||^2 \leq e^2, \tag{9}$$

where $\hat{x}$, y, H, and A respectively represent the restored image, the blocky image, the degradation operator, and a highpass filter for incorporating *a priori* smoothness constraint. There is no closed form solution for (8), since H is a nonlinear operation. With this observation, we propose a spatially adaptive regularized iterative restoration method. As a result of applying the proposed spatially adaptive constrints, the k-th regularized iteration step can be given as,

$$x_i^{k+1} = x_i^k + \beta e_i^T(b - T_i x^k), \quad \text{for } i = 1, 2, \cdots, N^2 \tag{10}$$

where

$$b = H^T y, \text{ and } T_i = H^T H + \lambda A_i^T A_i. \tag{11}$$

In (11), because H is nonlinear due to nonlinear rounding martirx R, implementations of $H^T y - H^T Hx$ and $H^T H$ are meaningless. Instead we approximate (11) as follows.

$$b = y, \text{ and } T_i = H + \lambda A_i^T A_i. \tag{12}$$

And, we assign one out of two different highpass filters, denoted by A_i, to each block, based on edge detection results.

The regularizing term in (12), denoted by $\lambda A_i^T A_i$, can be replaced by a lowpass filtering operation, as

$$x^{k+1} = \mathcal{G} \cdot \{x^k + \beta(y - Hx^k)\} \tag{13}$$

*In general, the space-invariant property results in block-Toeplitz degradation matrix. But in many image processing application, block-Toeplitz matrix is replaced by block-circulant with the size of the image is sufficiently large.

where $\mathcal{G}\cdot$ represents a spatially adaptive lowpass filter. More specifically, if a block is classified as monotone block, the corresponding lowpass filter has experimentally been chosen as

$$g_{mono} = \begin{bmatrix} 0.00 & 0.00 & 0.0751 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.1239 & 0.00 & 0.00 \\ 0.0751 & 0.1239 & 0.2042 & 0.1239 & 0.0751 \\ 0.00 & 0.00 & 0.1239 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.0751 & 0.00 & 0.00 \end{bmatrix}, \tag{14}$$

otherwise,

$$g_{edge} = \begin{bmatrix} 0.000 & 0.125 & 0.000 \\ 0.125 & 0.5 & 0.125 \\ 0.000 & 0.125 & 0.000 \end{bmatrix}, \tag{15}$$

and in (13) β_i represents the step length for monotone and edge blocks, β_{mono} takes the value between $0.01 \sim 0.3$ and β_{edge} $0.3 \sim 1.0$.

The detail process of the proposed block classification technique is described in the following subsection.

3.2. Block-based edge classification

In this subsection, we describe a simple block classification technique using a part of DCT coefficients, which is suitable for implementing the block-adaptive directional highpass filter in (9).

For a $B \times B$ image block, the corresponding DCT coefficients are expressed as,[9]

$$C_x(k_1, k_2) = \alpha(k_1) \cdot \alpha(k_2) \cdot \sum_{n_1=0}^{B-1} \sum_{n_2=0}^{B-1} x(n_1, n_2) \times \cos \frac{\pi}{2B} k_1(2n_1+1) \times \cos \frac{\pi}{2B} k_2(2n_2+1), \tag{16}$$

where

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{B}}, & \text{for } u = 0 \\ \sqrt{\frac{2}{B}}, & \text{for } u = 1, 2, ..., B-1. \end{cases} \tag{17}$$

For example, when the block size is 8×8, we use only $C(0,1)$ and $C(1,0)$ out of sixty four DCT coefficients, which represent the vertical and the horizontal edges, respectively. They are given as,

$$\begin{aligned} C_{ver} &= C(0,1) = \\ &\frac{\sqrt{2}}{8} \cdot \sum_{n_1=0}^{7} \sum_{n_2=0}^{7} x(n_1, n_2) \cos \frac{\pi}{2 \cdot 8}(2n_2+1), \\ C_{hor} &= C(1,0) = \\ &\frac{\sqrt{2}}{8} \cdot \sum_{n_1=0}^{7} \sum_{n_2=0}^{7} x(n_1, n_2) \cos \frac{\pi}{2 \cdot 8}(2n_1+1). \end{aligned} \tag{18}$$

Using those coefficients, we determine the direction of edge in each block. More specifically, array 8×8 block can be classified into monotonic or edge block. The edge classification algorithm is summarized in the following.

Algorithm 1 (Edge classification)

If $|C_{ver}| \leq \sigma^2$ and $|C_{hor}| \leq \sigma^2$, then the block is monotone,
else the block contains edge.

In Algorithm 1, σ is a sufficiently small positive quantity which controls the sensitivity of edge classification.

4. EXPERIMENTAL RESULTS AND CONCLUSIONS

The 512 × 512 Lena image was compressed, by using the quantization table shown in Fig. 2, and then reconstructed. Parts of the original and the compressed images are shown in Figs. 3 and 4, respectively.

At each iteration, each block is classified to either monotone or edge block. According to the classified edge information, one out of two different highpass filters is selected. And then adaptive iterative image restoration is performed according to the edge information. The resulting image by using the proposed algorithm is shown in Fig. 5.

We compare the proposed restored image with two conventional block artifact reduction method in the sense of edge variance, denoted by σ_e^2, that represents a measure of image blockiness,[10] and peak-to-peak signal-to-noise ratio (PSNR). Edge variance and PSNR of three deblocking algorithms are summarized in Table 1.[3,2] They are given respectively as

$$\sigma_e^2 = \sum (i_1 - i_2)^2, \tag{19}$$

and

$$PSNR = 10 \log_{10} \frac{N^2 \times 255^2}{\|f - f'\|} \tag{20}$$

where i_1 and i_2 represent intensity values of two pixels that are next to each other in the same row or column, but are in different blocks, f and f' the original image and the restored image, and N^2 the size of the image.

The proposed restoration method shows significant improvement in the sense of reducing blocking artifacts with well-preserved edge informations.

5. CONCLUSIONS

In this paper, we proposed an adaptive iterative image restoration method for reducing block artifacts in BDCT-based compressed images. The proposed algorithm shows better deblocking performance than the conventional algorithms in the sense of both reducing between block edge variance and preserving directional edges. Although the proposed restoration method can efficiently reduce block artifacts, the quality of the processed images cannot completely be equal to that of original one due to missing information in the quantization process. With minor modifications, the proposed method may be used as a post-processor in the decoder of video compression systems, such as digital VCR, video on demand, and digital HDTV systems.

6. ACKNOWLEDGEMENTS

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Blocking artifacts reduction method	Edge variance	PSNR [dB]
Original	2.08×10^6	-
Compressed image	3.51×10^6	31.45
Reeve's method	2.22×10^6	31.58
Rosenholtz' method	1.19×10^6	31.85
The proposed method	1.26×10^6	32.47

Table 1. Comparison of original, compressed, Reeve's, Rosenholtz' and the proposed image quality. proposed and Rosenholtz' method is assumed 5 iterations.

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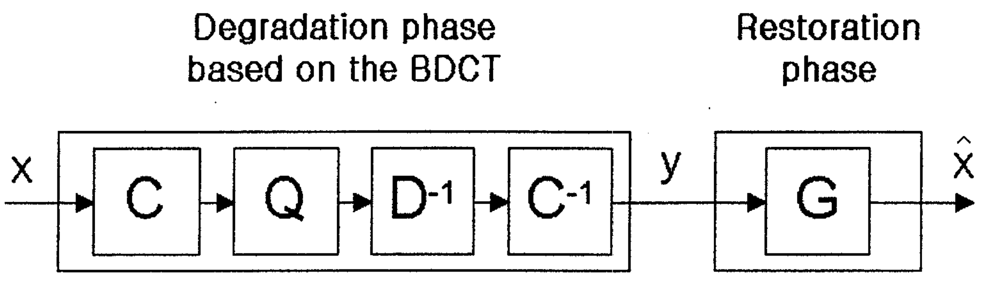

Figure 1. Block diagram of the image degradation-restoration model for the BDCT-based compression-reconstruction process.

	j=1	j=2	• • •					
i=1	50	60	70	70	90	120	255	255
i=2	60	60	70	96	130	255	255	255
⋮	70	70	80	120	200	255	255	255
	70	96	120	145	255	255	255	255
	90	130	200	255	255	255	255	255
	120	255	255	255	255	255	255	255
	255	255	255	255	255	255	255	255
	255	255	255	255	255	255	255	255

Figure 2. Quantization table used for JPEG-based compression.

Figure 3. A part of the original 256 × 256 Lena image.

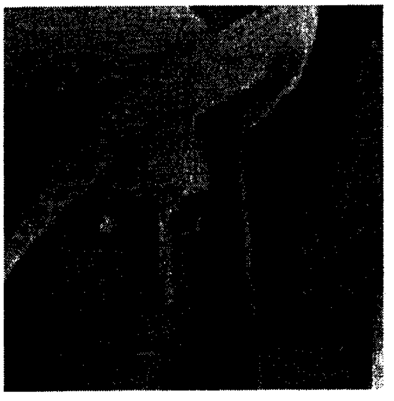

Figure 4. A part of the compressed 256 × 256 Lena image.

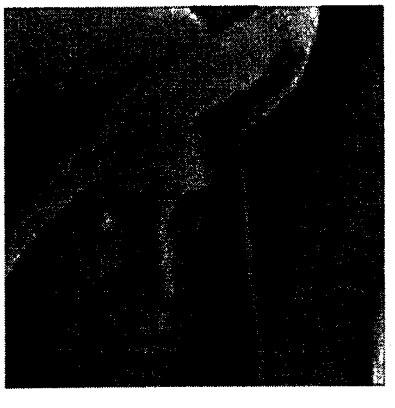

Figure 5. The block artifacts reduced image by using the proposed restoration method.