POCS-based Blocking Artifacts Suppression with Region Smoothness Constraints for Graphic Images

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Abstract

It is well known that low bit rate BDCT coded image exhibits visually annoying coding artifacts. In this paper, we proposed a POCS-based deblocking algorithm using a novel region smoothness constraint for the class of graphic images. For this type of images, there usually exist large smooth varying regions in the images. Current POCS based deblocking algorithms usually do not enforce smoothness across several blocks. In our method, the BDCT coded image is modeled using a smooth, spatially adaptive, thin-plate spline surface, and region smoothness constraint set is constructed from this spline surface. The spline modeling allows us to model the long range smoothness across smooth region. Simulation experiments indicated that blockiness in smooth regions is effectively suppressed while genuine edges are preserved.

1. Introduction

Block-based Discrete Cosine transform (BDCT) coding [1] is a widely used image compression technique. In BDCT coding, the DCT is applied to 8×8 non-overlapping image blocks, followed by quantization and entropy coding. However, the negligence of correlation among adjacent blocks causes visually annoying block discontinuities to be created along block boundaries. The truncation of high frequency DCT coefficients also produces ringing artifacts near strong edges.

A popular post-processing method for removing the blocking artifacts is the projection onto convex sets (POCS) algorithm [2-5]. The POCS method in [2] requires that the final deblocked image satisfy the quantization constraint and the block boundary smoothness constraint by bandlimiting the DCT coefficients with a lowpass filter. The bandlimiting process proposed in [2] is, however, not a projection. Thus, convergence of the algorithm cannot be guaranteed. In [3, 4], POCS is used to impose the quantization constraint and the image smoothness constraint across block boundaries, and satisfactory results have been obtained.

Recently, the smoothness constraint is been applied to the homogenous regions in an image, which can span across several blocks [5]. Thus, unlike smoothing across block boundaries, i.e., local and short range smoothing; region smoothing can be long range and is not limited by the

block size. However, a major requirement in [5] is that the images be consisted of planar regions.

In this paper, we describe a POCS-based deblocking algorithm for graphic images using a region smoothness constraint that can handle non-planar homogenous regions, i.e., we allow the intensity of homogenous region to vary smoothly. The algorithm is evaluated both visually and quantitatively and has been shown to perform well.

2. Smooth Region Modeling

The smooth region in an image is modeled using the thinplate spline [6]. A thin-plate spline f(x,y) is a smooth function which interpolates a surface at the landmark points $z(x_i, y_i)$. This function behaves like a thin metal plate and minimizes the total bending energy given by,

$$E = \iint_{\mathbb{R}^2} \left(\frac{\partial^2 f}{\partial x^2}\right)^2 + 2\left(\frac{\partial^2 f}{\partial x \partial y}\right)^2 + \left(\frac{\partial^2 f}{\partial y^2}\right)^2 dxdy \tag{1}$$

over the class of such interpolants. Given a set of points $\{z_i(x_i, y_i)\}_{i=1,\dots,m}$, the thin-plate spline takes the form

$$f(x,y) = \sum_{i=1}^{m} a_i K_i(x,y) + a_{m+1} + a_{m+2} x + a_{m+3} y$$
 (2)

where
$$K_i(x, y) = r_i^2(x, y) \log r_i^2(x, y)$$
 (3)

and
$$r_i(x, y) = \sqrt{(x - x_i)^2 + (y - y_i)^2}$$
 (4)

In a surface modeling problem using thin-plate spline, we are given a set of data points $\{z_i(x_i, y_i)\}_{i=1,\dots,m}$. The task is to construct a best-fit surface $f(x_i, y_i)$ with sufficient smoothness, i.e., one which minimizes the following regularized cost function

$$c(f) = \sum_{i=1}^{m} [z_i - f(x_i, y_i)]^2 + \lambda E$$
 (5)

where λ is a scalar that controls the smoothness of the surface. The coefficients a_i , i=1,...,m+3, in (2) are determined as the solution of the linear system Aa = z [6], where

$$A = \begin{bmatrix} K + \lambda I & P \\ P^T & 0 \end{bmatrix}, \quad a = \begin{bmatrix} a_1 \\ \vdots \\ a_m \\ a_{m+1} \\ a_{m+2} \\ a_{m+3} \end{bmatrix}, \quad z = \begin{bmatrix} z_1 \\ \vdots \\ z_m \\ 0 \\ 0 \\ 0 \end{bmatrix}$$
 (6)

with I the $m \times m$ identity matrix and,

$$K = \begin{bmatrix} K_{1}(x_{1}, y_{1}) & \cdots & K_{m}(x_{1}, y_{1}) \\ \vdots & & \vdots \\ K_{1}(x_{m}, y_{m}) & \cdots & K_{m}(x_{m}, y_{m}) \end{bmatrix}$$

$$P = \begin{bmatrix} 1 & x_{1} & y_{1} \\ \vdots & \vdots & \vdots \\ 1 & x_{m} & y_{m} \end{bmatrix}$$
(7)

3. The Deblocking Algorithm

3.1 Spline surface computation

A thin-plate spline surface for the entire image is obtained by stitching together the local thin-plate spline surfaces over each of the 8×8 block. To blend the local surfaces smoothly, the local surface computation is done over a larger block, and retaining only the surface in the center 8×8 block. Such an approach allows varying local smoothness to be imposed over each 8×8 block (by using different λ in (5)), depending on the high frequency content of the particular block.

We categorize the degree of smoothness of each 8×8 block into one of 4 classes, i.e., from 1 (least smooth) to 4 (smoothest). First, the standard deviations for every 16×16 blocks, *STD16*, and 8×8 blocks, *STD8*, are determined. Then, the following empirical rule is used,

If
$$STD8 \ge 10$$
, class = 1
Else-if $STD16 \le 5$, class = 4
Else-if $STD16 \le 10$, class = 3 (8)
Else class = 2

We set the smoothness parameter λ to 1, 10, 50, 100 for smoothness class equals to 1, 2, 3 and 4, respectively. Instead of fitting the spline surface over all image pixels, the surface is fitted using the data points derived from the compressed image, using the data point configurations shown in Fig.1. The data points in the interior of the block and at the four corners are computed by taking average of the centre pixel and its 4 neighborhoods. The data points along the four borders are computed by taking average of the centre pixel and its two neighboring pixels located along the direction orthogonal to the border.

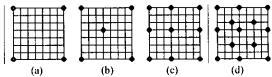


Fig.1. Data point configuration for (a) class 4, (b) class 3, (c) class 2, and (d) class 1.

The discontinuities along block boundaries could be due to real edges. It can be shown that the magnitude of mismatch between adjacent blocks is constrained by the DC quantization step size [7]. Specifically, the minimum block discontinuities, Δ_{min} , between adjacent blocks is given by Q(0,0)/8, where Q(0,0) is the DC entry in the quantization table. It was observed that the largest block discontinuity due to quantization is equal to $2\Delta_{min}$ for a ramp signal. Based on such observation, we flag the discontinuities along block boundaries as real edges when their magnitude is greater than $2.5\Delta_{min}$ and retain the image pixels along these real edges as data points. Once the data points are obtained, a spline surface can be constructed over the entire image.

3.2 The projection operators

In POCS-based image reconstruction, every known property of the original image f can be formulated as a corresponding convex set. The original image is then assumed to lie in the intersection of these convex sets, i.e.,

$$f \in C_0 = \bigcap_{i=1}^m C_i \tag{9}$$

The problem of reconstructing an image from its m properties is equivalent to that of finding an element in C_0 . If the projection operator P_i projecting onto the convex set C_i is realizable, the problem is recursively solvable.

The region smoothness constraint is applied to each of the 8×8 block. Let S_k be the spline surface for the block k and let ε_k be the error bound associated with block k. The region smoothness constraint set for block k is defined as

$$C_s^k = \left\{ f_k : \left\| f_k - S_k \right\| \le \varepsilon_k \right\} \tag{10}$$

The set C_s^k can be viewed geometrically as a closed hypersphere, with a radius of ε_k , and with its centre located at point S_k , in a 64-D space. It is obvious that the set C_s^k is convex and closed. From this geometrical viewpoint, it is easy to define the nearest projection of any point not in C_s^k onto the surface of this hyper-sphere. Let $g_k \notin C_s^k$ and $f_k \in C_s^k$, where f_k is the nearest projection of g_k onto . . . Define the ratio $\eta = \varepsilon_k / \|g_k - S_k\|$, then, by geometric argument, it can be easily shown that

$$f_k = \eta g_k + (1 - \eta) S_k \tag{11}$$

Therefore, the projection of g_k onto C_s^k , i.e., $P_S g_k = f_k$, can be realized as

$$f_k = \begin{cases} \eta g_k + (1 - \eta) S_k & \text{if } || g_k - S_k || > \varepsilon_k \\ g_k & \text{otherwise} \end{cases}$$
 (12)

The BDCT domain quantization constraint set for the 8×8 block can be expressed as [2],

$$C_Q = \left\{ f : \hat{F}_i^{\min} \le (Df)_i \le \hat{F}_i^{\max}, \forall i = 1, 2, ..., 64 \right\}$$
 (13)

where \hat{F} are the quantized BDCT coefficients of the image f, D is the BDCT transformation matrix, \hat{F}_i^{\min} and \hat{F}_i^{\max} are the i-th minimum and maximum allowable BDCT coefficients as determined by the quantizer's i-th quantization interval Δ_i and the i-th quantized BDCT coefficient \hat{F}_i , i.e.,

$$\hat{F}_{i}^{\text{nún}} = \hat{F}_{i} \Delta_{i} - 0.5 \Delta_{i}$$

$$\hat{F}_{i}^{\text{max}} = \hat{F}_{i} \Delta_{i} + 0.5 \Delta_{i}$$
(14)

The projection of f onto the set C_Q is given by

$$P_O f = D^T D f = D^T F (15)$$

where
$$F_{i} = \begin{cases} \hat{F}_{i}^{\min} & \text{if } (Df)_{i} < \hat{F}_{i}^{\min} \\ \hat{F}_{i}^{\max} & \text{if } (Df)_{i} > \hat{F}_{i}^{\max} \\ (Df)_{i} & \text{otherwise} \end{cases}$$
 (16)

As the intensity of the original image is assumed to lie between 0 and 255, a range constraint set can be defined as,

$$C_R = \left\{ f : 0 \le f_1 \le 255, \ j = 1, \dots, n_1 n_2 \right\}$$
 (17)

where n_1n_2 is the dimension of the image. The projection onto C_R , $P_R g = f$, can be realized as

$$f_j = \begin{cases} 0 & \text{if } g_j < 0\\ 255 & \text{if } g_j > 0255\\ g_j & \text{otherwise} \end{cases}$$
 (18)

The deblocked image is obtained by iterating

$$f_n = P_R P_O P_S f_{n-1} \tag{19}$$

with f_0 given by the thin-plate spline image S, until convergence is reached.

4. Experimental Results

The proposed algorithm has been tested on BDCT coded graphic images containing smooth regions. For illustration purpose, we present the deblocking results of computergenerated graphic images "SHELL" and "KNOT" in Fig.2 and Fig.3, respectively. One can see that blockiness in smooth region is effectively suppressed without compromising the sharpness of the edges. For quantitative comparison, we compared with Zakhor's algorithm [2], and the MPEG4 algorithm [8], the PSNR for the two methods are 33.83dB and 35.72dB for SHELL, and 33.18dB and 34.90dB for KNOT, respectively. Our method clearly outperforms these two methods, both in terms of PSNR and visual quality.

5. Conclusions

In this paper, we proposed a POCS-based deblocking algorithm for graphic images using a novel region smoothness constraint, where the homogenous regions in an image are modeled as a smooth, spatially adaptive thinplate spline surface. The region smoothness constraint allows long range smoothness to be applied to homogenous regions, instead of just across block boundaries. Unlike our previous work [5], the homogenous regions are not restricted to be planar. The proposed algorithm is especially suited to computer-generated graphics, where the long range region smoothness assumption is well satisfied. Experiments indicate that blockiness in homogenous regions can be suppressed effectively, while genuine edges are preserved.

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References

- [1] N. Ahmad, T. Natarajan, and K.R. Rao, "Discrete Cosine Transform Coding of Images", IEEE Trans. Computer, vol. 23, pp. 90-93, 1941.
- [2] A. Zakhor, "Iterative Procedures for Reduction of Blocking Effects in Transform Image Coding", IEEE Trans. Circuits and System for Video Technology, vol. 2, no. 1, pp. 91-95, March 1992.
- [3] Y. Yang, N.P. Galatsanos, and A.K. Katsaggelos, "Regularized Reconstruction to Reduce Blocking Artifacts of Block Discrete Cosine Transform Compressed Images", IEEE Trans. Circuits and System for Video Technology, vol. 3, no. 6, pp. 431-442, Dec. 1993
- [4] Y. Yang and N.P. Galatsanos, "Projection-Based Spatially Adaptive Reconstruction of Block-Transform Compressed Images", IEEE Trans. Image Processing, vol. 4, no. 7, pp. 896-908, July 1995.
- [5] C. Weerasinghe, A.W.C. Liew and H. Yan, "Artifact Reduction in Compressed Images based on Region Homogeneity Constraints using the Projections onto Convex Sets Algorithm", IEEE Trans. Circuits and Systems for Video Technology, Vo. 12, No. 10, Oct 2002, pp. 891-897.
- [6] F.L. Bookstein, "Principal Warps: Thin-plate Splines and the Decomposition of Deformations", IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 11, no. 6, pp. 567-585, June 1989.
- [7] A.W.C. Liew and H. Yan, "Blocking Artifacts Suppression in Block-Coded Images Using Overcomplete Wavelet Representation", IEEE Trans. Circuits and Systems for Video Technology, Vol. 14, No. 4, pp.450-461, April 2004.
- [8] MPEG 4 Verification Model, VM 14.2, 1999, pp. 260 264.

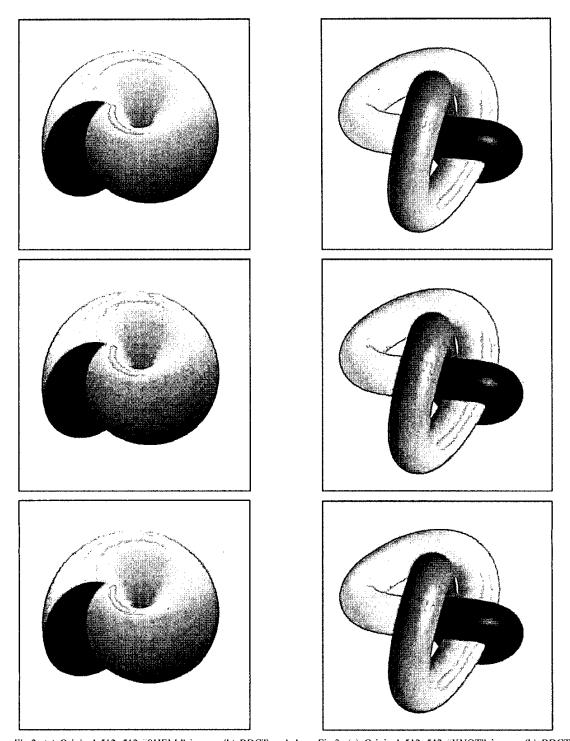


Fig.2. (a) Original 512×512 "SHELL" image, (b) BDCT coded image (34.94 dB), (c) Deblocked image (37.51 dB).

Fig.3. (a) Original 512×512 "KNOT" image, (b) BDCT coded image (34.22 dB), (c) Deblocked image (36.33 dB).