MODIFIED POINTWISE SHAPE-ADAPTIVE DCT FOR HIGH-QUALITY DEBLOCKING OF COMPRESSED IMAGES

Chandan Singh D. Rawat, Rohan K. Shambharkar, Sukadev Meher

Abstract— Blocking artifact is one of the most annoying artifacts in the image compression coding. In order to improve the quality of the reconstructed image several deblocking algorithms have been proposed. A high-quality modified image deblocking algorithm based on the shape-adaptive DCT (SA-DCT) is shown. The SA-DCT is a low-complexity transform which can be computed on a support of arbitrary shape. This transform has been adopted by the MPEG-4 standard and it is found implemented in modern video hardware. This approach has been used for the deblocking of block-DCT compressed images. In this paper we see modified pointwise SA-DCT method based on adaptive DCT threshold coefficient instead of constant DCT threshold coefficient used by the original pointwise SA-DCT method. Extensive simulation experiments attest the advanced performance of the proposed filtering method. The visual quality of the estimates is high, with sharp detail preservation, clean edges. Blocking artifacts are suppressed while salient image features are preserved.

Index Terms— Anisotropic, DCT threshold coefficient, Debloking, SA-DCT.

I. INTRODUCTION

The new JPEG-2000 image compression standard solved many of the drawbacks of its predecessor. The use of a wavelet transform computed globally on the whole image, as opposed to the localized block-DCT (B-DCT) (employed e.g. by the classic JPEG), does not introduce any blocking artifacts and allows it to achieve a very good image quality even at high compression rates. Unfortunately, this new standard has received so far only very limited endorsement from digital camera manufacturers and software developers. As a matter of fact, the classic JPEG still dominates the consumer market and the near-totality of pictures circulated on the internet is compressed using this old standard. Moreover, the B-DCT is the work-horse on which even the latest MPEG video coding standards rely upon. There are no convincing indicators suggesting that the current trend is about to change any time soon. All these facts, together with the ever growing consumer demand for high quality imaging, makes the development of advanced and efficient post-processing (deblocking) techniques a very actual and relevant application area.

In this paper a modified pointwise SA-DCT method for the restoration of B-DCT compressed grayscale images is proposed. It is based on the pointwise shape-adaptive DCT (SA-DCT) [14] approach and its characterized by a high quality of the filtered estimate.

The SA-DCT [1, 2] is a generalization of the usual separable block-DCT (B-DCT) which can be computed on a support of arbitrary shape. It is obtained by cascaded application of one-dimensional varying-length DCT transforms first on the columns and then on the rows that constitute the considered support. Thus, it retains the same computational complexity of the B-DCT. The SA-DCT has been originally developed for coding non-rectangular image patches near the border of image objects, in such a way to minimize the stored information and to avoid the ringing artifacts (Gibbs phenomenon) that would appear in correspondence with strong edges. Because of its low complexity, the near-optimal de-correlation and energy compaction properties (e.g. [1], [5]), and its backward compatibility with the B-DCT, the SA-DCT has been included in the MPEG-4 standard [3], where it is used for the coding of image segments that lie on the video-object’s boundary. The recent availability of low-power hardware SA-DCT platforms (e.g. [2], [6]) makes this transform an appealing choice for many image-and video-processing tasks.

The first attempt to use of SA-DCT for image denoising was reported by the authors in [7]. The original version of the method has been adapted for image

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deblocking. These algorithms demonstrate a remarkable performance, typically outperforming the best methods known to the authors. The SA-DCT estimates have also been shown to achieve one of the highest subjective visual quality [8].

The paper is organized as follows. In the sections 2 to 5 a brief overview on the basic anisotropic LPA-ICI in conjunction with SA-DCT method [14] is shown. In section 6 we see the proposed modified pointwise SA-DCT method based on adaptive DCT threshold coefficient. In Section 7 the adaptation of the denoising algorithm to deblowing [14] is seen and to relate the quantization table with the value of the variance to be used for the filtering. The final Section is devoted to extensive experimental results by considering different types of quantization tables, several level of compression, for grayscale images.

II. ANISOTROPIC LPA-ICI

Noisy observations $z$ of the form is given by,

$$z(x) = y(x) + \eta(x)$$  

(1)

where $y$ is the original image, $\eta(x) \sim N(0,\sigma^2)$ is independent Gaussian white noise, $x$ is a spatial variable belonging to the image domain $X \subset \mathbb{Z}^2$. we restrict ourself to grayscale images (and, thus, scalar functions).

Here only a brief overview on the original method developed for image denoising is shown and refer the reader to [14] (and references therein) for a more formal, complete, and rigorous description.

The use of a transform with a shape-adaptive support involves actually two separate problems: not only the transform should adapt to the shape (i.e. a shape-adaptive transform), but the shape itself must adapt to the image features (i.e. an adaptive shape). The first problem has found a very satisfactory solution in the SA-DCT transform [1, 2]. The second problem is essentially application-dependant. It must be noted that conventional segmentation (or local-segmentation) techniques which are employed for video processing (e.g. [10]) are not suitable for degraded (noisy, blurred, highly compressed, etc.) data. In this approach, the SA-DCT in conjunction with the anisotropic LPA-ICI technique [11, 12, 13] is used. The approach is based on a method originally developed for pointwise adaptive estimation of 1-D signals [12, 13]. The technique has been generalized for 2-D image processing, where adaptive-size quadrant windows have been used [16]. Significant improvement of this approach has been achieved on the basis of anisotropic directional estimation [7, 11]. Multidirectional sectorial-neighborhood estimates are calculated for every point. Thus, the estimator is anisotropic and the shape of its support adapts to the structures present in the image. In Fig. 1, some examples of these anisotropic neighborhoods for the Lena and Cameraman images are shown. The developed anisotropic estimates are highly sensitive with respect to change points, and allow to reveal fine elements of images from noisy observations.

![Fig. 1. Anisotropic LPA-ICI. From left to right: Sectorial structure of the anisotropic neighborhood achieved by combining a number of adaptive-scale directional windows; some of these windows selected by the ICI for the noisy Lena and Cameraman images [14].](image)

III. SHAPE-ADAPTIVE DCT

SA-DCT [1, 2] is computed by cascaded application of 1-D varying-length DCT transforms first on columns and then on rows that constitute the considered region as shown in Fig 2. This approach concerns normalization of transform and subtraction of the mean and which have a fundamental impact on the use of the SA-DCT for image filtering.

![Fig. 2. Illustration of the shape-adaptive DCT transform and its inverse. Transformation is computed by cascaded application of 1-D varying-length DCT transforms, along the columns and along the rows [14].](image)

A. Orthonormal Shape-Adaptive DCT

The normalization of the SA-DCT is obtained by normalization of the individual 1-D transforms that are used for transforming the columns and rows. In terms of their basis elements, they are defined as

$$\sqrt{\frac{D}{L}}DCT(r) = c_m \cos \left( \frac{\pi m (2n + 1)}{2L} \right)$$

$$m, n = 0, \ldots, L - 1$$

$$c_m = \sqrt{1/L}, c_m = \sqrt{2/\pi}, m > 0.$$  

(2)

Here, $L$ stands for the length of the column or row to be transformed. The normalization in (2) is, indeed, the most natural choice, since in this way all the transforms used are orthonormal and the corresponding matrices belong to the orthogonal group. Therefore, the SA-DCT—which can be obtained by composing two orthogonal matrices—is itself an orthonormal transform. A different normalization of the 1-D transforms would produce, on an arbitrary shape, a 2-D
transform that is nonorthogonal (for example, as in [1] and [2], where \( c_0 = \sqrt{2/L} \) and \( c_m = 2/L \) for \( m > 0 \)).

Here \( T_U : U \rightarrow V_U \) is the orthonormal SA-DCT transform obtained for a region \( U \subset X \), where \( U = \{ f : U \rightarrow \mathbb{R} \} \) and \( V_U = \{ \varphi : V_U \rightarrow \mathbb{R} \} \) are function spaces and \( V_U \subset \mathbb{R}^{2} \) indicates the domain of the transform coefficients. \( T_U^{-1} : V_U \rightarrow U \) is the inverse transform of \( T_U \).

The thresholding (or quantization) operator is indicated as \( \gamma \). Thus, the SA-DCT-domain processing of the observations on a region \( U \) is written as

\[
\hat{y}_U = T_U^{-1}(\gamma(T_U(z_U))) = T_U^{-1}(\gamma(U_U(z_U))) + \bar{n}_U = T_U^{-1}(\gamma(U_U(z_U))) + \bar{n}_U
\]

where \( \bar{n}_U = T_U^{-1}(\gamma(U_U(z_U))) \) is again Gaussian white noise with variance \( \sigma^2 \) and zero mean.

**B. Mean Subtraction**

There is an adverse consequence of the normalization (2). Even if the signal restricted to the shape is constant, the reconstructed is usually non-constant. In [5] this behavior is termed as “mean weighting defect,” and it is proposed there to attenuate its impact by applying the orthonormal SA-DCT on the zero-mean data which is obtained by subtracting from the initial data its mean. After the inversion, the mean is added back to the reconstructed signal \( \hat{y}_U : U \rightarrow \mathbb{R} \)

\[
\hat{y}_U = T_U^{-1}(\gamma(U_U(z_U))) + m_U(z)
\]

where \( m_U(z) = (1/|U|) \sum_{x \in U} z(x) \) is the mean of \( z \) on \( U \).

**IV. POINTWISE ANISOTROPIC LPA-ICI + SA-DCT**

The anisotropic adaptive neighborhoods \( \tilde{U}_k \) defined by the LPA-ICI as supports for the SA-DCT, as shown in Fig. 3 is used. By demanding the local fit of a polynomial model, the presence of singularities or discontinuities within the transform support can be avoided. In this way, it can be ensured that data are represented sparsely in the transform domain, significantly improving the effectiveness of thresholding.

**A. Fast implementation of the LPA-ICI anisotropic neighborhoods**

Narrow 1-D “linewise” directional LPA kernels \( \{ g_{k,\theta} \}_{k=1,2,3,5,7,9} \) are used for \( k = 8 \) directions, and after the ICI-based selection of the adaptive-scales \( \{ h^+(x,\theta_k) \}_{k=1}^{8} \) the neighborhood \( \tilde{U}_k \) is the octagon constructed as the polygonal hull of \( \{ \text{supp } g_{k,\theta} : k=1 \ldots 8 \} \). Such neighborhoods are shown in Fig. 4.

**B. Thresholding in SA-DCT domain**

An illustration of the SA-DCT-domain hard-thresholding, performed according to (2) is given in Fig. 5.

\[
\hat{y}_U = T_U^{-1}(\gamma(U_U(z_U))) + m_U(z)
\]

where \( m_U(z) = (1/|U|) \sum_{x \in U} z(x) \) is the mean of \( z \) on \( U \).

**V. THRESHOLDING IN SA-DCT DOMAIN**

An illustration of the SA-DCT-domain hard-thresholding, performed according to (2) is given in Fig. 5.

**A. Thresholding in SA-DCT domain: Local Estimate**

For every point \( x \in X \), a local estimate \( \hat{y}_{U_k} : \tilde{U}_k \rightarrow \mathbb{R} \) of the signal \( y \) is constructed by thresholding in SA-DCT domain as in (3)

\[
\hat{y}_{U_k} = T_{U_k}^{-1}(\gamma(T_{U_k}(z_{U_k} - m_{U_k}(z)))) + m_{U_k}(z)
\]

where \( \gamma_k \) is a hard thresholding-operator based on the universal threshold,

\[
\sigma = \sqrt{2 \ln |U_k|} + 1
\]

**B. Thresholding in SA-DCT domain: Global Estimate**

All the local estimates (4) are averaged together using adaptive weights (7) that depend on their local variances and on the size of the corresponding adaptive-shape regions.
\[ y = \frac{\sum_{x \in X} w_x y_{z|x}^+ |x|}{\sum_{x \in X} w_x x_{z|x}^+} \]
\[ w_{x|z} = \frac{\sigma^{-2}}{(1 + N_{z,x}^h)} u_{x|z}^+ \]

(7)

C. Wiener filtering in SA-DCT domain: Local Estimate

Once a global estimate of the signal is available, it is used as a reference signal in order to perform Wiener filtering in SA-DCT domain which is given by,

\[ y_{z|x}^+ = T_{u|x}^{-1} \left( w_{x \phi_{z,x}} + \sigma^2 m_{u|x}^+ (z) \right) \]

(8)

D. Wiener filtering in SA-DCT domain: Global Estimate

All the local Wiener estimates (8) are averaged together using adaptive weights (10) that depend on the size of the corresponding adaptive-shape regions.

\[ y_{z|x}^+ = \frac{\sum_{x \in X} w_{x \phi_{z,x}} y_{z|x}^+ |x|}{\sum_{x \in X} w_{x \phi_{z,x}} x_{z|x}^+} \]

(9)

\[ w_{x|z}^+ = \frac{1}{\sigma^2 + \sum_{z \in z} w_{z|z}^+ u_{z}^+} \]

(10)

VI. PROPOSED MODIFIED POINTWISE SADCT ALGORITHM

From (4), the threshold coefficient for DCT for local estimate is calculated as

\[ \gamma = \text{DCT threshold coefficient} \times \alpha \sqrt{2 \ln |\sigma^2| + 1}. \]

(11)

where \( \sigma \) is the standard deviation and \( u_{z|x}^+ \) is an adaptive-shape neighbourhood as shown in Figure 3.

The author has used DCT threshold coefficient \( \text{DCThrCOEF} = 0.925 \) (constant). We propose a more adaptive method. The reconstructed image \( y_U \) which is restricted to the shape \( z_U \) (Figure 3) from hard thresholding is given by

\[ y_U = T_U^{-1} \left( T_U \left( z_U - m_U(z) \right) \right) + m_U(z) \]

(12)

where \( T_U \) is the orthonormal SA-DCT transform for a region \( U \) and \( \gamma \) is the thresholding coefficient and \( m_U(z) \) is its mean.

From the above relation we conclude that \( y_U \) is dependent on \( \gamma \) and \( m_U(z) \).

We propose to use value of \( \gamma \) dependent on MSE (Mean Squared Error) of image and MAX (Maximum Absolute Difference).

First we calculate the value of MAX and MSE. Several experiments were carried out using Lena, Peppers and Barbara image of size 512 x 512 on MATLAB platform on a 1.6 GHz Intel(R) CPU. For B-DCT quantization, if the value of MAX and MSE is less than 90 then thresholding coefficient is 0.9. If the value of MAX is greater than 90 and the value of MSE is between 100 to 120 or greater than 250 then thresholding coefficient is 0.9. If the value of MAX is greater than 90 and the value of MSE is greater than 120 or less than 80 then the thresholding coefficient is 1.01. For JPEG compression if the value of MSE is less than 90 then the thresholding coefficient is 0.9 or else it is 1.01. Thus in our modified case the DCT thr coef is 1.01 or 0.9 depending on MSE and MAX.

VII. POINTWISE SA-DCT FOR B-DCT ARTIFACTS REMOVAL

More sophisticated models of B-DCT-domain quantization noise have been proposed by many authors, here we model this degradation as some additive Gaussian white noise. In this section we restrict our attention to the grayscale/single-channel case and thus assume the observation model

\[ z = y + n \]

(13)

where \( y \) is the original (non-compressed) image, \( z \) its observation after quantization in B-DCT domain, and \( n \) is independent Gaussian with variance \( \sigma^2 \), \( n \sim N(0, \sigma^2) \).

We estimate a suitable value for the variance \( \sigma^2 \) directly from the quantization table \( Q = [q_{ij}], i = 1,...,8 \) using the following empirical formula:

\[ \sigma^2 = 0.69 \cdot \left( \frac{1}{9} \sum_{i,j=1}^{3} q_{i,j} \right)^{1.3} \]

(14)

This formula uses only the mean value of the nine table entries which correspond to the lowest-frequency DCT harmonics (including the DC-term) and has been experimentally verified to be quite robust for a wide range of different quantization tables and images. A higher compression obviously corresponds to a larger value for the variance.

The \( \sigma^2 \) which is calculated by (14) is not an estimate of the variance of compressed image, nor it is an estimate of the variance of the difference between original and compressed images. Instead, it is simply the variance of the white Gaussian noise \( n \) in the observation model (13). It is the variance of some hypothetical noise which, if added to the original image \( y \), would require - in order to be removed - the same level of adaptive smoothing which is necessary to
suppress the artifacts generated by the B-DCT quantization with the table $Q$. 

Figure 6: Details of the JPEG-compressed grayscale Lena ($Q=6$, PSNR=28.24dB) and Pointwise SA-DCT estimate (PSNR=29.8671dB) and of the corresponding modified Pointwise SA-DCT estimate (PSNR=29.8679dB). The estimated standard deviation for this highly compressed image is $\sigma=17.6$.

Figures 6, and 7 shows the JPEG compressed grayscale Lena image obtained for two different compression levels (JPEG quality $Q=6$ and $Q=15$) as used in original SADCT method [14] and the corresponding SA-DCT filtered estimates and our modified estimates. For these two cases the estimated standard deviations are $\sigma=17.6$ and $\sigma=9.7$.

VIII. EXPERIMENTAL RESULTS

Extensive simulation experiments were carried out. Consequently, we present comparative numerical results collected in two separate tables. The two tables contain results for grayscale images obtained using particular quantization tables found in the literature (Table 1) and JPEG (Table 2).

Three quantization tables - usually called $Q_1$, $Q_2$, and $Q_3$ - have been used by many authors (e.g. [15] and references therein) in order to simulate various types of B-DCT compression. For identifying the considered quantization tables, the first row of each table is shown below:

$$
Q_1(1\cdots8,1) = [50 \ 60 \ 70 \ 70 \ 90 \ 120 \ 255 \ 255],
Q_2(1\cdots8,1) = [86 \ 59 \ 54 \ 86 \ 129 \ 216 \ 255 \ 255],
Q_3(1\cdots8,1) = [110 \ 130 \ 150 \ 192 \ 255 \ 255 \ 255 \ 255].
$$

The values of the standard deviation $\sigma$ corresponding to these three tables - calculated using formula (4) - are 12.62, 13.21, and 22.73, respectively.

In terms of image degradation, they correspond to a medium to high compression level, similar to what can be obtained by using JPEG with $Q = 11$ ($Q_1$), $Q = 9$ ($Q_2$), or $Q = 5$ ($Q_3$).

In Table 1 we present results for deblocking from B DCT quantization performed using these specific quantization tables. We compare the results obtained by the SA-DCT algorithm against the best results obtained by any of the methods [17, 18, 19, 20, 21, 22], as reported in [17]. We use Lena, Peppers and Barbara image of size $512 \times 512$ for comparison our modified SA-DCT algorithm against the original SA-DCT algorithm. The results are in favor of our proposed technique.

Further positive results are shown in Table 2 for the case of deblocking from JPEG-compression. In this second table comparison is shown between SA-DCT against the best result obtained by any of the methods [23, 24, 25, 26, 27, 19], as reported in [23] and we compare the modified pointwise SA-DCT method against the original pointwise SA-DCT method. Also in this comparison, our modified Pointwise SA-DCT method is found to be superior to all other methods.

IX. CONCLUSION

We proposed a new method of selecting DCT threshold coefficient depending on the MSE (Mean Squared Error) of the image and MAX (Maximum Absolute Difference) instead of taking it constant as in the original pointwise SA-DCT method. Our modified pointwise SA-DCT approach with adaptive DCT threshold coefficient gives better result than the original pointwise SA-DCT method with constant DCT threshold coefficient.
Table 1: PSNR (dB) comparison table for restoration from B-DCT quantization for three different quantization matrices. The values of best results correspond to any of the methods[17, 18, 19, 20, 21, 22] as reported in [17] and the value of original Pointwise SA-DCT method is compared with our modified Pointwise SA-DCT method.

<table>
<thead>
<tr>
<th>Qua</th>
<th>Lena</th>
<th>Peppers</th>
<th>Barbara</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>31.70</td>
<td>31.63</td>
<td>32.1256</td>
</tr>
</tbody>
</table>

Table 2: PSNR (dB) comparison table for restoration from JPEG compression of grayscale images. The values of best results correspond to any of the methods[23, 24, 25, 26, 27, 19] as reported in [23] and the value of original Pointwise SA-DCT method is compared with our modified Pointwise SA-DCT method.

<table>
<thead>
<tr>
<th>Qua</th>
<th>Lena</th>
<th>Peppers</th>
<th>Barbara</th>
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<tr>
<td>12</td>
<td>30.09</td>
<td>31.79</td>
<td>32.4774</td>
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</table>

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