Removing the Blocking Artifacts of Block-Based DCT Compressed Images

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***Abstract*—One of the major drawbacks of the block-based DCT compression methods is that they may result in visible artifacts at block boundaries due to coarse quantization of the coefficients. In this paper, we propose an adaptive approach which performs blockiness reduction in both the DCT and spatial domains to reduce the block-to-block discontinuities. For smooth regions, our method takes advantage of the fact that the original pixel levels in the same block provide continuity and we use this property and the correlation between the neighboring blocks to reduce the discontinuity of the pixels across the boundaries. For texture and edge regions we apply an edge-preserving smoothing filter. Simulation results show that the proposed algorithm significantly reduces the blocking artifacts of still and video images as judged by both objective and subjective measures.**

***Index Terms*—Blocking artifacts, JPEG, low bit rate coding, MPEG, post-processing.**

I. Introduction

BLOCK-BASED DCT coding has been successfully used in image and video compression applications due to its energy compacting property and relative ease of implementation. After segmenting an image into blocks of size N × N, the blocks are independently DCT transformed, quantized, coded, and transmitted. One of the most noticeable degradation of the block transform coding is the "blocking artifact." These artifacts appear as a regular pattern of visible block boundaries. This degradation is a direct result of the coarse quantization of the coefficients and of the independent processing of the blocks which does not take into account the existing correlations among adjacent blocks pixels.

To cope with the blockiness problem, different types of post-filtering techniques are developed to reduce the high frequency components near the block boundaries. These methods can be classified as spatial filtering methods [1]–[4], DCT-based filtering methods [5]–[7] or hybrid filtering methods [8]–[13]. Earlier on, Reeve and Lim [1] proposed a symmetric, two-dimensional Gaussian spatial filtering method. However, due to its low-pass nature, this spatial filtering approach has the drawback of visible smoothing of the image. To try to minimize this blurring, various other schemes have been suggested.

In [3], [4], and [8]–[11], an edge classification procedure is used to distinguish between monotone, textured and strong edge regions of the image. The spatial filtering scheme is driven by the output of these edge classifiers. Edge and texture regions are usually not filtered since humans are more sensitive to low frequency errors than to high frequency ones. The edge classification is done in the spatial or in the DCT domain. In [3] and [4] spatial methods such as the gradient/threshold and the histogram methods are used. In [8]–[11], the block classification is performed by examining the DCT coefficients.

Projection onto convex sets (POCS) based recovery algorithm [12] is a powerful DCT domain filtering approach. The basic idea is to optimize the value of the quantized transform coefficients, subject to some smoothness and quantization constraints. The major drawback of this approach is its high computational complexity. It takes at least 3∼5 iterations for this algorithm to converge, where both forward and inverse DCT are required in each iteration, in addition to other required computational overhead.

A filtering strategy, which relies on the estimation of the quantization error T for each $n \times n$ spatial block is proposed in [13]. T is determined by the quantization step and the probability distribution of the original unquantized DCT coefficients. The latter is estimated from the moments of the quantized coefficients. To alleviate the discontinuity offset problem caused by smoothing the boundary pixels, the smoothing process is repeated until the center of the block is reached. Because of quantization, it is difficult to get a good estimate of the probability distribution of the DCT coefficient at each frequency. If we cannot get an accurate estimate of T for each block, we may risk over-smoothing or under-smoothing in the filtering process.

While the above mentioned methods carry their computations in the spatial or both spatial and DCT domains, many DCT-based methods have also been proposed. In [5], the blocking effects are reduced in the DCT domain by suppressing the block-DCT coefficients. The suppression parameters are determined from the distribution of the DCT coefficients in the coding process.

In [6], the transform coefficients are estimated using the local statistics of the quantized coefficients. The reconstructed transform coefficients are confined to their original quantization intervals. The above two methods require no iterations.

In this paper, we propose a new DCT based method for reducing the blocking effects in smooth regions of the image. Our

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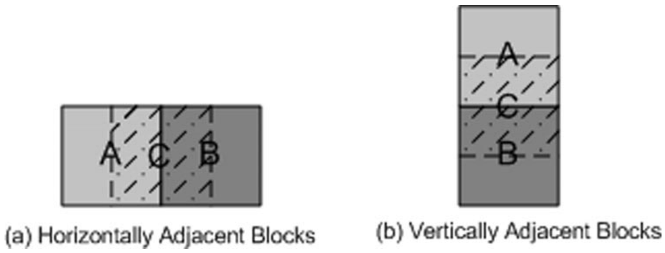

Fig. 1. Blockiness diagram.

method takes advantage of the fact that some of the DCT coefficients of a step function (a sharp edge) have nonzero values. This fact was also independently observed by Zeng [7]. However, the method we propose for deblockiness is totally different from that of [7]. In [7], good results are obtained at very low bit rates, i.e., for images with high blockiness effects, otherwise artifacts will appear. Our method expands the range of smoothing the blockiness effects to include the case when the blockiness appearance is not as strong. We use the existing correlation information between the existing blocks so as not to introduce artifacts. We explore the correlation between the intensity values of the boundary pixels of two neighboring blocks in the DCT domain. The continuity of the pixels across the boundary is recovered from the continuity of the pixels of the two neighboring blocks. For the strong texture and edge regions, the nature of the frequencies of the two neighboring blocks differ from each other. Thus this approach introduces artifacts in these nonsmooth regions. Therefore our first step is to detect these regions based on the frequency coefficients. If the two 8×8 neighboring blocks of a boundary have similar frequency properties and the 8×8 pixel area around the boundary does not have high frequencies then the latter area is declared to be of smooth nature. In this case, DCT filtering which ensures pixel values continuity is applied to this 8×8 pixel area. For the nonsmooth regions, a noise smoothing but edge preserving filter is applied. The Sigma filter is shown to have good performance in these regions. It removes the artifacts while preserving the true edges and texture. In Section II below we study the DCT coefficients of a strong edge and in Section III we show how to modify these coefficients so as to remove blockiness but not introduce artifacts.

II. Frequency Representation of the Spatial Block Discontinuity in the DCT Domain

We examine two (8×8 pixels) adjacent blocks A and B, and assume block A has a constant gray value a and block B has a constant gray value b ($a \neq b$), see Fig. 1. Here, we study the case of the horizontally adjacent-blocks, i.e, the left hand side of Fig. 1. For the vertical adjacent blocks the same principles apply. Let the right half of block A and the left half of block B form a block denoted as block C. Block C is the 8×8 block which contains the boundary pixels. Therefore, there is a horizontal step inside block C. Let $F_a(u,v)$, $F_b(u,v)$ and $F_c(u,v)$ be the DCT coefficients of block A, B and C. Since the pixels of blocks A and B have constant intensity values, each of $F_a(u,v)$ and $F_b(u,v)$ has only one nonzero value which is at (0,0). Block C has discontinuity in the middle of the block. Its DCT coefficients $F_c(u,v)$ are

$$F_c(u,v) = C_u C_v \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} c(k,l) W_{DTC}(u,k) W_{DCT}(v,l) \tag{1}$$

where $c(k,l)$ is the intensity of the (k,l) pixel in C, C_u, C_v, and W_{DCT} are given by

$$C_u, C_v = \begin{cases} \frac{1}{\sqrt{N}} & for\ u=0, v=0, \\ \sqrt{\frac{2}{N}} & otherwise, \end{cases}$$
$$W_{DCT}(u,k) = \cos\left[(2k+1)\frac{\pi u}{2N}\right].$$

Note that since $c(k,l)$ forms a step function, (1) can be rewritten as

$$F_c(u,v) = C_u C_v \sum_{l=0}^{N-1} c(k,l) W_{DCT}(v,l) \sum_{k=0}^{N-1} W_{DCT}(u,k) \tag{2}$$

If $u \neq 0$, then $\sum_{k=0}^{N-1} W_{DCT}(u,k) = 0$. That is $F_c(u,v) = 0$ for $u \neq 0$. If $u = 0$, then $\sum_{k=0}^{N-1} W_{DCT}(u,k) = N$. Thus $F_c(u,v) = C_u C_v N \sum_{l=0}^{N-1} c(k,l) W_{DCT}(v,l)$ for $u = 0$. For $\mathrm{N} = 8$, we have

$$\begin{aligned}
F_c(u,v) &= C_u C_v N \sum_{l=0}^{7} c(k,l) W_{DCT}(v,l) \\
&= C_u C_v N \left(\sum_{l=0}^{3} a \bullet W_{DCT}(v,l) \right. \\
&\qquad \left. + \sum_{l=4}^{7} b \bullet W_{DCT(v,l)} \right) \\
&= a C_u C_v N \sum_{l=0}^{7} W_{DCT}(v,l) \\
&\quad + (b-a) C_u C_v N \sum_{l=4}^{7} W_{DCT}(v,l) \\
&= (b-a) C_u C_v N \sum_{l=4}^{7} W_{DCT}(v,l) \\
&= (b-a) C_u C_v N \left(\cos\frac{9}{8}v\pi + \cos\frac{11}{8}v\pi \right. \\
&\qquad \left. + \cos\frac{13}{8}v\pi + \cos\frac{15}{8}v\pi \right).
\end{aligned} \tag{3}$$

It can be calculated from (3) that $F_c(u,v) = 0$ for $v = 2, 4, 6$.

Therefore, $F_c(u,v)$ has nonzero values only for $v = 0, 1, 3, 5, 7$ and $u = 0$. This implies that the noise energy of the horizontal boundary discontinuity of block C is represented only in some coefficients of the first row of the DCT coefficient array. It also can be easily deduced that the heavier the blockiness, the larger the ripples in these nonzero values.

III. Recovering the Continuity of Block C in the DCT Domain

The above results suggest that in order to reduce the blocking effect between two horizontally adjacent (8 × 8) blocks, $F_c(u,v)$ for $v = 0$, 1, 3, 5, 7 and $u = 0$ should be modified. Theses modifications should be carried so as to reduce the blockiness effect and at the same time preserve the original information of the image. In [7], the zero-masking method is proposed. This method basically suppresses the amplitudes of some of the odd numbered DCT coefficients. However altering the values of these coefficients without taking into consideration the information about the nature of the image in that neighborhood might result in artifacts. This is specially the case for high bit rate applications. Thus the filtering should adapt to the local information content of the image. Before such filtering is performed, one has to ensure that the edge appearance (blockiness) between blocks A and B is not due to a genuine horizontal change in the grey levels of the pictures at that position. Thus the conditions that should be met before modifying the blockiness appearance of the relatively smooth regions are:

1) Block A has a similar horizontal frequency property as block B.
2) The boundary between block A and block B belongs to a relatively smooth region.

To meet condition (1) above, the first row of the DCT matrix of block A and that of block B should be close in values. However as discussed in [9] and [10], the coefficients in the 3 × 3 top left corner of the DCT coefficient matrix are good representatives of the block frequency property. This is because most of the image energy is compacted in these low frequencies. Thus, to save on the number of computations and to meet the first condition above, we only impose the following two constraints:

$$\text{a. } |F_a(0,0) - F_b(0,0)| < T_1 \tag{4}$$

$$\text{b. } |F_a(0,1) - F_b(0,1)| < T_2. \tag{5}$$

To address condition (2) above we note that if there is a strong edge between block A and block B, this edge appears in block C. Thus, for condition (2) to be satisfied, we also have to make sure that block C is of low frequency content. The presence of texture or strong diagonal edges would result in relatively high values of the high order DCT coefficients. However, from our experiments we found that to save on the number of computations it is enough to meet the following constraint:

$$\text{c. } |F_c(3,3)| < T_3. \tag{6}$$

Please note that T_1, T_2, and T_3 are all predetermined i.e. fixed thresholds. According to our simulations, we found that $T_1 = 350$, $T_2 = 120$ and $T_3 = 60$ gave the best results. The selection of these thresholds are based on the observation of the blockiness and experiments. The choice of the thresholds are image and compression ratio dependent. However, the selection of these values are not critical. The results are very close when the values are chosen within ±15% range. For very low bit rates the above scheme results in more aggressive filtering than in the case of higher bit rates.

If the three constraints above are satisfied, we perform the blockiness reduction in the DCT domain by modifying the five relevant coefficients of $F_c(u,v)$. The first row of the DCT coefficient matrix of block C is modified by the weighted average of blocks A, B, and C. The advantage of using weighted average of adjacent block coefficients to modify the AC coefficients of block C, instead of simply reducing the values of these coefficients, is that it is much more adaptive to image contents. In the very low bit rate encoding, the AC coefficients in blocks A and B have small values due to quantization. This is also true for stationary regions. Thus in these cases, our method yields similar results as that of Zeng's zero-masking scheme. But for the higher bit rate encoding cases or for texture regions, our method can still preserve certain AC values.

Let $F_{Mc}(u,v)$ be the modified DCT coefficient of block C. The modification is formulated as follows:

$$F_{Mc}(0,v) = \alpha_0 F_c(0,v) + \beta_0 \left[F_a(0,v) + F_b(0,v)\right],$$

where

$$v = 0, 1 \tag{7}$$

$$F_{Mc}(0,v) = \alpha_1 F_c(0,v) + \beta_1 \left[F_a(0,v) + F_b(0,v)\right]$$

where

$$v = 3, 5, 7 \tag{8}$$

$$F_{Mc}(u,v) = F_c(u,v) \quad \text{for all} \quad v \neq 0, 1, 3, 5, 7 \tag{9}$$

where $\alpha_0 + 2\beta_0 = 1$ and $\alpha_1 + 2\beta_1 = 1$. In our experiments, $\alpha_0 = 0.6$, $\beta_0 = 0.2$ and $\alpha_1 = 0.5$, $\beta_1 = 0.25$.

Then the pixels of block $C(k,l)$, are replaced by $C_{Mc}(k,l)$, the inverse DCT of $F_{Mc}(u,v)$. It can be easily shown that the modified gray levels of the pixels of block C are

$$C_{Mc}(k,l) = c(k,l) + \xi(l) \tag{10}$$

where

$$\begin{aligned}\xi(l) &= \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} (C_u C_v \left(F_{Mc}(u,v) - F_c(u,v)\right) \\ &\qquad \times W_{DCT}(u,k) W_{DCT}(v,l)) \\ &= C_0 C_0 \left[F_{Mc}(0,0) - F_c(0,0)\right] \\ &\quad + \sum_{i=0}^{3} C_0 C_v \left[F_{Mc}(0,v) - F_c(0,v)\right] \\ &\quad \times W_{DCT}(v,l)\end{aligned} \tag{11}$$

where $v = 2i + 1$.

The processing procedure described above is used to reduce the discontinuity at the boundary of two horizontally adjacent blocks. A similar procedure can be used to remove the boundary discontinuity between two vertically adjacent blocks. In the latter case, the first column of the DCT coefficient array of block C is modified.

The above method removes the edges of the blocks in the stationary regions affected by the blockiness effects. For the strong texture and edge regions we do not perform the above filtering so as to avoid the appearance of artifacts. In order to remove the blocking effects that might have remained and improve on other encoding artifacts such as ringing effects and uneven appearance in stationary areas which are due to quantization, we apply

Fig. 2. Original Lena image.

Fig. 3. Post-processed Lena original image by our algorithm.

Fig. 4. Decompressed Lena image, bitrate $= 0.297$ bpp.

Fig. 5. Post-processed Lena decompressed image by our algorithm.

an edge-preserving smoothing spatial filter. There are numerous excellent filters such as [14]–[17]. Here, we apply the Sigma filter [16] due to its simplicity. The value of the threshold used in our simulation was equal to 5. Applying such a filter preserves the edges and smoothes the noise, resulting in a more pleasing appearance. The improvements in the edge areas are obvious in still images but are not as noticeable in video sequence as motion tends to mask some of the blocking and encoding artifacts.

IV. Results and Conclusions

We have applied the proposed algorithm on JPEG still images and on MPEG-2 video sequences. The latter was displayed in real time on a television. The subjective results as viewed by many people were judged to be very good for still images and marginally improved for video images. Fig. 2 shows the original Lena image and Fig. 4 shows the decoded JPEG Lena image at 0.297 bpp. In order to show our filter's adaptive capability, we apply the same filter to both images. The post-processing of the original image obtained by our method is shown in Fig. 3. As shown, our post processing filter does not introduce smoothing into the image. The post processing of the decoded image is shown in Fig. 5. As we can see most of the blocking artifacts in the decoded image after post-processing using our filter are removed. However, since blocking effects are less noticeable in the texture regions, especially in video streams, the spatial filtering step could be omitted for video applications. Our method can efficiently eliminate blocking effects for images coded at different bit rates without producing noticeable artifacts. It smooths out the undesired block edges while retaining the sharpness of the decoded image to a noticeable degree.

The main attraction of our algorithm is that it can highly preserve the high frequency components while smoothing out the blocking artifacts. This is because only the DCT coefficients related to the blocking artifact are modified while other frequency components remain the same. Our algorithm requires a fairly low computational effort. For each block the number of computations is very close to that of computing the 2-D DCT for each block. Thus it is useful for real-time applications.

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