MEASURING BLOCKING ARTIFACTS USING EDGE DIRECTION INFORMATION

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ABSTRACT
Block-based transform coding is the most popular approach for image and video compression. The objective measurement of blocking artifacts plays an important role in the design, optimization, and assessment of image and video coding systems. This paper presents a new algorithm for measuring blocking artifacts in images and videos. Instead of using the traditional pixel discontinuity along the block boundary, we use the edge directional information of the images. The new algorithm does not need the exact location of the block boundary thus is invariant to the displacement, rotation and scaling of the images. Experiments on various still images and videos show that the new blockiness measure is very efficient in terms of computational complexity and memory usage, and can produce blocking artifacts measurement consistent with subjective rating.

1. INTRODUCTION
Block transform coding is the most popular approach for image and video coding. Most of the current image and video coding standards, such as JPEG, H.26x and MPEG-1/2/4, make use of the block-based discrete cosine transform (BDCT) [1]. In BDCT coding, DCT coefficients are calculated over small non-overlapping blocks, and the 2-D blocks of transform coefficients are then quantized. In the decoder, the quantized transform coefficients are de-quantized, and inverse transformed to recover the original data (with certain distortion). At low bit rate image and video coding, a large quantization value is used. Therefore, the decompressed image and video exhibits various kinds of distorted artifacts. One of the most noticeable artifacts is the “blocking artifact,” which is an artificial discontinuity between adjacent blocks and is a direct result of the independent quantization of the BDCT coefficients [2-6]. However, blocking artifacts are structural disturbance, and are sometimes “buried” in the massively accumulated across-the-board pixel-wise error. Therefore their significance in perceptual visual quality assessment is not reflected correctly in the conventional PSNR (peak signal-to-noise ratio) measure. An effective measure of blocking artifacts can be used as a quality metric alone [3-5] or a factor in quality evaluation [2,6,7].

There are generally two types of objective image and video quality metrics, i.e., referenced and un-referenced approach. In a referenced approach, the access to original images is required. By using the original and reproduced image as inputs, the system outputs a numerical value that quantifies the visibility of blocking artifacts in the reproduced image [3]. This approach is not very useful in applications such as image and video communication, where original image and video is not accessible. On the other hand, the un-referenced approach [4, 5] is of more interests because of its computational efficiency and wider scopes of potential applications, including in-service visual quality monitoring and post-processing for decoded signal. However, designing un-referenced objective quality metrics is very difficult due to the limited understanding of the human vision system (HVS). It is believed that effective un-referenced objective quality metrics are only feasible when the prior knowledge about the image distortion types is available [2-5].

The generalized block-edge impairment metric $M_{GBIM}$ proposed in [4] evaluates the visual significance of block-edge artifacts in a given image by taking into account the luminance masking effects in extreme bright/dark areas in a reconstructed image. Wang [5] has proposed an un-referenced perceptual quality assessment of JPEG compressed images based on the measures of blockiness and image signal activity, and these two measures are then combined in a model whose parameters are estimated from the subject test data.

In this paper, a new algorithm is proposed to calculate the blocking artifacts in BDCT-coded image and video. Compared with the existing algorithms, this new method does not need the exact location of the block boundary thus is invariant to the displacement, rotation and scaling of the images. The method will also provide the information as to if and how the images have been altered. Experiments on various still images and videos show that the new measure can produce consistent prediction of blockiness.

The rest of the paper is organized as follows. Section 2 presents the un-referenced approach for measuring blocking artifacts in BDCT coded images based on the edge directional information. Section 3 presents the experimental results, and its comparison with some of the existing schemes. Section 4 provides the conclusions of the paper.
2. EDGE DIRECTION BASED BLOCKING ARTIFACTS MEASUREMENT

As mentioned in the Introduction, the blocking artifacts manifest itself as an artificial discontinuity between neighboring blocks. This is the direct result of the high quantization value used in the encoding process, and the independent processing of these blocks that does not take into account the cross-block pixel correlations. A typical phenomenon of blocking artifacts is that the inter-pixel differences of cross-block pixels are much bigger than that of the in-block pixels. In this section, we will discuss another important impact of the BDCT coding on the images, i.e., the changes in the pixel edge orientation and its relationship with the blocking artifacts caused by the BDCT coding.

2.1. Edge direction histogram and blocking artifacts

As mentioned previously, when the blocking artifacts become severe, discontinuity between neighboring blocks becomes more obvious. This is only the change of the amplitude of the pixel. By examining the edge orientation of those pixels in an 8×8 block as shown in Figure 1, we can notice that the edge orientation of these pixels will change accordingly as the quantization values used in BDCT coding increases. For example, those pixels marked with ‘H’ will tend to have edge orientation of 0°, those marked with ‘V’ will tend to have edge orientation of 90°, and those marked with ‘D’ will tend to have edge orientation in the diagonal direction. As to the pixels marked with ‘Z,’ their edge intensity will become smaller and smaller due to the loss of high frequency details. Therefore, by examining the edge orientation changes of these pixels we will be able to find how severe the blocking artifacts are.

![Figure 1. Edge orientations of pixels in an 8×8 block](image1)

Figure 1. Edge orientations of pixels in an 8×8 block.

Figure 2 shows the edge direction histograms of original image “Lena” and its BDCT coded counterpart (PSNR = 35.21dB). From this figure we can see that these two images have similar edge direction histograms in most of the other edge directions, except that the BDCT coded image has very strong edge direction presences at 0° and 90°, which is the result of the abrupt inter-pixel discontinuity of cross-block pixels in the horizontal direction and vertical direction. It is also noted that as the blocking artifacts become more severe, more and more pixel edges will align in these two directions. Therefore the proportion of the orientation of edges along these two directions in an image is a very good indication how severe the blocking artifacts are.

![Figure 2. Edge direction histograms of “Lena” and its BDCT coded images](image2)

Figure 2. Edge direction histograms of “Lena” and its BDCT coded images.

2.2. Construction of the edge direction histogram

The pixel gradient vectors in an image are determined by the gradient vector \( \left[ G_x(x, y), G_y(x, y) \right] \), which can be approximated by using the following Sobel operation [9]:

\[
G_x(x, y) = I(x-1, y) + 2I(x, y+1) + I(x+1, y+1) - I(x-1, y-1) - 2I(x, y-1) - I(x+1, y-1)
\]

\[
G_y(x, y) = I(x+1, y-1) + 2I(x+1, y) + I(x+1, y+1) - I(x-1, y-1) - 2I(x-1, y) - I(x-1, y+1)
\]

\[ (1) \]

![Figure 3. Edge direction histograms of “Lena” and its BDCT coded images after rotating 10°](image3)

Figure 3. Edge direction histograms of “Lena” and its BDCT coded images after rotating 10°.
where $I(x,y)$ represents the pixel intensity at location $(x,y)$ in an image. In order to reduce the noise effect caused by the digitization of the images, the edge direction histogram is based on the local average of the pixel gradient vectors. However the gradients cannot be directly averaged in local neighborhood since opposite gradient vectors will then cancel each other, though they are indicating the same edge orientation [8]. One solution to this problem is to square the complex number representation of the vectors before averaging, which is equivalent to doubling the angles of the gradient vectors. After doubling the angles, opposite gradient vectors will point to the same direction and therefore will reinforce each other, while perpendicular gradients will cancel each other. After averaging, the gradient vectors have to be converted back to their single-angle representation. The squared vectors are found as,

$$\bar{G}_x + j \bar{G}_y = G_x^2 - G_y^2 + j 2G_xG_y$$  \hspace{1cm} (2)

and the average squared gradient can be calculated by averaging in local neighborhood, using a possible non-uniform window $W$,

$$DF_x = \sum W \left(G_x^2 + G_y^2\right), \quad DF_y = \sum W \left(2G_xG_y\right)$$  \hspace{1cm} (3)

Now, the averaged gradient direction, $\phi$, with $0 \leq \phi \leq 180$, is given by,

$$\phi(x,y) = \begin{cases} 180, & DF_x = 0 \cap DF_y = 0 \\ \frac{\arctan \left(\frac{DF_x}{DF_y}\right)}{\pi}, & \text{elsewhere} \end{cases}$$  \hspace{1cm} (4)

Therefore, the edge direction histogram is defined as,

$$Hist(k) = Hist(k) + 1, \quad \text{if } \phi(x,y) = k, \text{ and } k \in [0,180]$$  \hspace{1cm} (5)

Note that $\phi = 180$ is a special case. It does not mean that the pixel’s edge orientation is in the horizontal direction the same as $\phi = 0$. Instead, it indicates that there is no intensity change around this pixel. And thus it is an indication of the local activities of the image signal. Figure 2 and Figure 3 show the examples of edge direction histograms.

2.3. Measuring blocking artifacts using edge direction information

Typically, BDCT coding will result in high discontinuity between neighboring blocks and it will also reduce the local activities of the image signal inside the blocks. After deriving the edge direction histogram as defined in Equation (5), we are able to define the blocking artifacts metrics based on the edge directional information.

As we have mentioned previously, the horizontal discontinuity between neighboring blocks will cause the pixel edge orientation concentrating towards $90^\circ$, and vertical discontinuity between neighboring blocks will cause the pixel edge orientation concentrating towards $0^\circ$. Therefore the population of the pixels with either $0^\circ$ or $90^\circ$ orientations indicates how severe the discontinuity, or the blocking artifacts is.

Thus, we define the horizontal and vertical discontinuity measures as,

$$B_{\text{IMAGE}} = \frac{\text{histo}(0) + \text{histo}(90)}{N_T \times 36} = \frac{\text{histo}(0) + \text{histo}(90)}{0.375 \times N_T}$$  \hspace{1cm} (6)

where the coefficient 0.375 is determined by the percentage of pixels in the 8x8 block as in Figure 1 marked with ‘H’ and ‘V’, and $N_T$ is the total number of pixels in the image.

Note again that for $\phi = 180$, histo(180) is an indication of the local activities of the image signal. Therefore, the signal activity measure of the image is defined as,

$$Z_{\text{IMAGE}} = \frac{\text{histo}(180)}{N_T \times 36} = \frac{\text{histo}(180)}{0.5625 \times N_T}$$  \hspace{1cm} (7)

Similarly the coefficient 0.5625 is determined by the percentage of pixels in the 8x8 block marked with ‘Z’. Although both $B_{\text{IMAGE}}$ and $Z_{\text{IMAGE}}$ give an indication of how severe the blocking artifacts are, their values are affected differently by the high quantization values. As the bits per pixel drop at certain value, $B_{\text{IMAGE}}$ starts dropping and $Z_{\text{IMAGE}}$ starts increasing, indicating that the blocking artifacts become less severe due to the fact that many blocks merge and large uniform areas have been created, and the local activities have been reduced due to high quantization values. On the other hand, for some pictures with large uniform areas such as clouds, sea, or walls etc, $Z_{\text{IMAGE}}$ is very big even though the image is coded at very high bit rate. Based on the above analysis, we have chosen the following model to combine the above two individual measures to constitute a distortion assessment model,

$$D_{\text{IMAGE}} = B_{\text{IMAGE}} + \beta \times B_{\text{IMAGE}} \times Z_{\text{IMAGE}}$$  \hspace{1cm} (8)

where the parameter $\beta$ is determined experimentally to provide a better correlation with the subjective assessment of the distortion. In our experiments, we noticed that $\beta=1.64$ gives the best correlation with the subjective test data. It should be pointed out that $D_{\text{IMAGE}}$ is not very sensitive to the variation of $\beta$ when it is within the range of 1 to 2.

It should also be noted that the above distortion metric is applicable to BDCT coded images without rotation. To apply $D_{\text{IMAGE}}$ to BDCT coded images with rotation such as the case in Figure 3, we then need to change the angles used in Equation (6) to be the two maximum cells which are $90^\circ$ apart. That is, we only need an extra step to find the maximum cells in the edge direction histogram before applying Equation (6). Equation (7) and (8) keep unchanged in this case.

3. EXPERIMENTS

In the following experiments, we used a number of still images, as well as frames from the test video sequences to test the performance of our algorithm. These images have
different resolutions, ranging from 176×144 to 512×512. Also, we use the 3×3 uniform window to perform the gradient averaging. Figure 4 shows the experimental results of applying \(DF_{IMAGE}\) to different images with different spatial complexity and resolution. It can be shown from these results that in general, \(DF_{IMAGE}\) achieves consistent results for all these images.

We have also tested our algorithm using the JPEG distortion database provided by LIVE [10]. The Pearson Correlation and Spearman rank-order Correlation between \(DF_{IMAGE}\) and the subjective ratings of the JPEG database are -0.9202 and 0.9036 respectively. After polynomial fitting, the fitted Pearson Correlation and Spearman rank-order Correlation between \(DF_{IMAGE}\) and the subjective ratings of the JPEG database are 0.9324 and 0.9042 respectively. This result shows that \(DF_{IMAGE}\) is very consistent with subjective ratings and thus is a very effective way of describing the subjective quality objectively. Figure 5 shows the scatter plot of applying \(DF_{IMAGE}\) to the images in LIVE database.

4. CONCLUSIONS

This paper presents a novel un-referenced approach for measuring blocking artifacts in BDCT coding. Instead of using the traditional pixel discontinuity along the block boundary, we use the edge directional information of the images. Therefore the new algorithm does not need the exact location of the block boundary and is thus invariant to the displacement, rotation and scaling of the images. An additional advantage of the proposed measure is its well-defined value range and being very simple computationally.

Experiments show that the new distortion measure exhibits consistent results with various types of images and frame in video sequences. The new measure can be used as a distortion metric, a contributing factor in a quality metric, or a parameter controlling an encoding/post-processing process in real-time, in both referenced and un-referenced situations.

5. REFERENCES