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ORIGINAL ARTICLE

Using edge direction information for measuring blocking artifacts of images

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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.

Keywords Image compression · Block-based transform coding · Perceptual metrics · Blocking artefacts · Un-referenced metrics

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1 Introduction

Block transform coding is the most popular approach for image and video coding. Most of the state of the art 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) (Shi and Sun, 1999). In BDCT coding, DCT coefficients are calculated over small non-overlapping blocks, and the 2D blocks of transform coefficients are then quantized, zigzag scanned, and entropy coded. 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 step size 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 transform coefficients (Karunasekera & Kingsbury, 1995; Miyahara, Kotani, Algazi, 1998; VQEG, 2000; Wang et al., 2002; Wu & Yuen, 1997). These 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 peak signal-to-noise ratio (PSNR) measure. An effective measure of blocking artifacts is indispensable and can be used as a quality metric alone (Karunasekera & Kingsbury, 1995; Wang et al., 2002; Wu & Yuen, 1997) or one of many factors in quality evaluation (Miyahara, Kotani, Algazi, 1998; VQEG, 2000; Yu, Wu, Winkler, Chen, 2002).

There are generally two types of objective image and video quality metrics, i.e., referenced approach 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 (Karunasekera & Kingsbury, 1995). 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 (Wang et al., 2002; Wu & Yuen, 1997) 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 (Karunasekera & Kingsbury, 1995; VQEG, 2000; Wang et al., 2002; Wu & Yuen, 1997).

The generalized block-edge impairment metric M_{GBIM} proposed in Wu and Yuen (1997) 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 et al. (2002) 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 video frames show that the new measure can produce consistent blockiness measures for images of different types and subject to different amount of compression.

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 large quantization step size 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 orientation changes of the edge pixels and their 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 due to the change of the amplitude of the pixel. By examining the edge orientation of those pixels in the boundary of 8×8 blocks as shown in Fig. 1, we can notice that the edge orientation of these pixels will change accordingly as the quantization values used in BDCT coding increases. Typically, as the quantization value increases, the blocking artifacts become more severe, and more and more edge pixels align in the orientation of 0° and 90°, or become inactive or "flat." Figure 2 shows an example of such trend for image "Mandrill." It is noted that the number of pixels that have the orientation of 0° and 90°, or "flat" increase monotonically as the quantization value increases, which is interpreted as the bits-per-pixel decreases in Fig. 2.

Figure 3 shows the pixel arrangement of an 8×8 block. It is obvious that, as is manifested in Fig. 3, 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 direction changes of these pixels we will be able to find how severe the blocking artifacts are.

Figures 4 and 5 shows the edge direction histograms of original image "Lena," "Mandrill," and their BDCT coded counterpart. From these figures we can see that these images and their BDCT coded counterparts have similar edge direction histograms in most of the other edge directions, except that the BDCT coded images have 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,

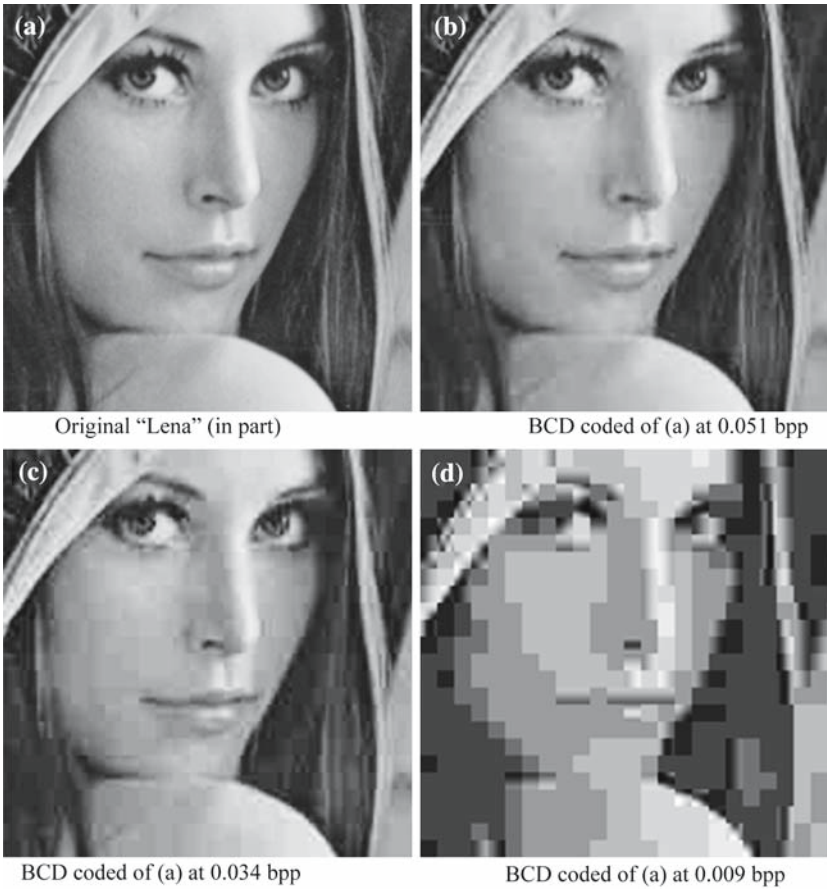

Fig. 1 The pixels' edge orientation change as the quantization values used in BDCT coding increases. (a) Original "Lena" (in part) (b) BCD coded of (a) at 0.051 bpp (c) BCD coded of (a) at 0.034 bpp (d) BCD coded of (a) at 0.009 bpp

Fig. 2 More and more pixels align in the edge orientation of 0°, 90°, or become "flat"

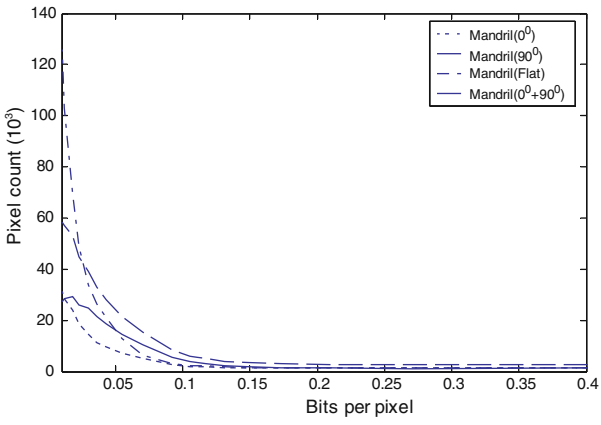

Fig. 3 Edge orientations of pixels in an 8×8 block

D	H	H	H	H	H	H	D
V	Z	Z	Z	Z	Z	Z	V
V	Z	Z	Z	Z	Z	Z	V
V	Z	Z	Z	Z	Z	Z	V
V	Z	Z	Z	Z	Z	Z	V
V	Z	Z	Z	Z	Z	Z	V
V	Z	Z	Z	Z	Z	Z	V
D	H	H	H	H	H	H	D

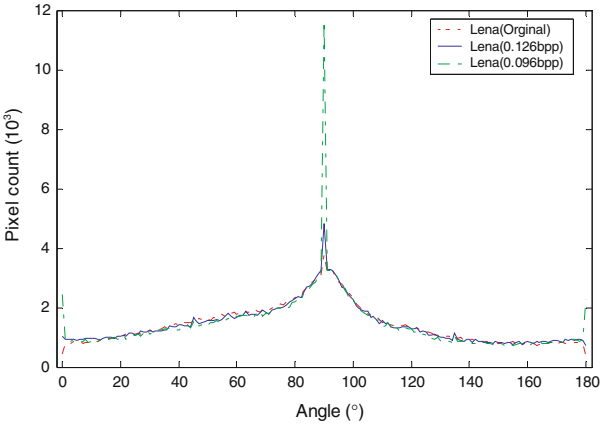

Fig. 4 Edge direction histograms of "Lena" and its BDCT coded image

more and more edge pixels will align in these two directions, and more pixels become inactive or "flat." Therefore the proportion of the orientation of edges along these two directions as well as becoming "flat" in an image is a very good indication how severe the blocking artifacts are.

A very interesting and useful feature of the edge direction histogram is that, if the BDCT coded image is rotated at angle α, there are still two strong edge direction presences around the angle $(\alpha + 0°)$ and $(\alpha + 90°)$. Note that the amplitude of these two spikes has been reduced and their width has been increased. This indicates that there is similar amount of energy around these two angles. It is noted that the reduction in the amplitude and increase in the width is basically due to the discrete nature of the images. Figure 6 shows the edge direction histograms of "Lena" and its BDCT coded image after rotating 10°.

2.2 Construction of the edge direction histogram

The pixel gradient vectors in an image are determined by the gradient vector $\left[G_x(x, y), G_y(x, y)\right]^T$, which can be approximated by using the following Sobel operator (Gonzalez & Woods, 2002):

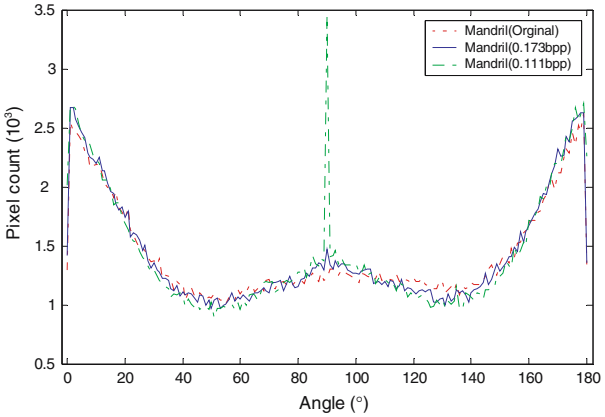

Fig. 5 Edge direction histograms of "Mandrill" and its BDCT coded image

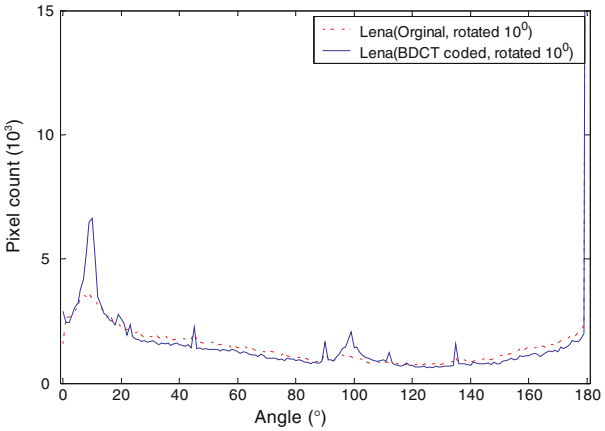

Fig. 6 Edge direction histograms of "Lena" and its BDCT coded images after rotating 10°

$$
\begin{aligned}
G_x(x,y) &= -I(x-1,y-1) - 2\times I(x-1,y) - I(x-1,y+1) \\
&\quad + I(x+1,y-1) + 2\times I(x+1,y) + I(x+1,y+1), \\
G_y(x,y) &= I(x-1,y+1) + 2\times I(x,y+1) + I(x+1,y+1) \\
&\quad - I(x-1,y-1) - 2\times I(x,y-1) - I(x+1,y-1),
\end{aligned} \tag{1}
$$

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. The purpose of "averaging" the gradient vectors is to cancel vectors when they are perpendicular to each other, and to reinforce each other when they are pointing to the same direction or pointing to the opposite direction, as the opposite gradient vectors indicate the same edge orientation. A well established solution to this problem is to double the angles of the gradient vectors before averaging (Bazen & Gerez, 2002; Kass & Witkin, 1987). After doubling the angles, opposite gradient vectors will point to the same direction and reinforce each other, while perpendicular gradients will cancel each other. For

example, two perpendicular vectors with 0° and 90°, will have orientation of 0° and 180° after doubling their angles, and will cancel each other after averaging, and opposite vectors with 0° and 180°, will have orientation of 0° and 360° after doubling, and will reinforce each other when averaged.

Mathematically, doubling the angles is equivalent to squaring the complex number representation of the gradient vectors. Note that the length of the gradient vectors is squared, which has the effect that strong orientations have a higher votes in the average orientation than weaker orientations before averaging, which is equivalent to doubling the angles of the gradient vectors.

$$\left(G_x + jG_y\right)^2 = G_x^2 - G_y^2 + j2G_xG_y \tag{2}$$

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

$$DF_x = \sum_{\mathrm{W}} \left(G_x^2 - G_y^2\right), \quad DF_y = \sum_{\mathrm{W}} \left(2G_xG_y\right). \tag{3}$$

Now, the averaged gradient direction ϕ, with $-90° \leq \varphi \leq 90°$, is defined as

$$\varphi\left(x, y\right) = \frac{1}{2}\angle\left(DF_x, DF_y\right), \tag{4}$$

where $\angle$(x,y) is defined as,

$$\angle(x, y) = \begin{cases} \frac{180°}{\pi}\tan^{-1}\left(\frac{y}{x}\right) & x \geq 0, \\ \frac{180°}{\pi}\tan^{-1}\left(\frac{y}{x}\right) + 180° & \text{for } x < 0 \wedge y \geq 0, \\ \frac{180°}{\pi}\tan^{-1}\left(\frac{y}{x}\right) - 180° & x < 0 \wedge y < 0 \end{cases} \tag{5}$$

and the edge direction, $\theta(x, y)$, which is perpendicular to the gradient direction, is defined as,

$$\theta\left(x, y\right) = \varphi\left(x, y\right) + 90°. \tag{6}$$

Note that the about angle, $\theta(x, y)$, has a range from 0° to 180°. Actually in our application it does not matter if the angle is 0° or 180°, as both indicate that the edge direction are in the horizontal direction. Therefore we will combine these two angles as follows,

$$\theta\left(x, y\right) = 0°, \quad \text{if } \theta\left(x, y\right) = 180°. \tag{7}$$

When both DF_x, DF_y are equal to zero, the pixel does not point to any direction but is an indication that the "activity" of the pixel is zero, or there is no intensity change around this pixel—these pixels are named "flat pixel." For the convenience of calculation of the edge direction histogram, we assign a special angle, 180°, to it,

$$\theta\left(x, y\right) = 180°, \quad \text{if } DF_x = 0 \text{ and } DF_y = 0. \tag{8}$$

Therefore the edge direction histogram is defined as,

$$\begin{aligned} \mathrm{Histo}(k) &= \mathrm{Histo}(k) + 1, \\ &\text{if } \theta(x, y) = k, \text{ and } k \in \left[0,\ 180\right]. \end{aligned} \tag{9}$$

Figures 5 and 6 show the examples of edge direction histograms.

2.3 Measuring blocking artifacts using edge direction information

Typically, BDCT coding will result in discontinuity between neighboring blocks and also reduce the local activities of the image signal inside the blocks, thus reduce the image quality. This is more obvious when large quantization values are used during the coding process. Therefore we are able to define the blocking artifacts metrics based on the edge directional information after deriving the edge direction histogram as defined in Eq. 9.

As we have mentioned previously, the horizontal discontinuity between neighboring blocks will cause the edge pixel's orientation concentrating toward 90°, and vertical discontinuity between neighboring blocks will cause the edge pixel's orientation concentrating toward 0°. Therefore the percentage of the pixels with either 0° or 90° orientations indicates how severe the blocking artifacts are.

We define the horizontal and vertical discontinuity measures as,

$$B_{\mathrm{IMAGE}} = \frac{\mathrm{histo}(0) + \mathrm{histo}(90)}{N_{\mathrm{T}} \times \frac{24}{64}} = \frac{\mathrm{histo}(0) + \mathrm{histo}(90)}{0.375 \times N_{\mathrm{T}}}, \tag{10}$$

where N_{T} is the total number of pixels in the image, and the coefficient 0.375 is a normalization factor that is determined by the percentage of pixels in the 8×8 block (as in Fig. 3) marked with "H" and "V."

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

$$\mathrm{Z}_{\mathrm{IMAGE}} = \frac{\mathrm{histo}(180)}{N_{\mathrm{T}} \times \frac{36}{64}} = \frac{\mathrm{histo}(180)}{0.5625 \times N_{\mathrm{T}}}. \tag{11}$$

Similarly the coefficient 0.5625 is a normalization factor that is determined by the percentage of pixels in the 8×8 block marked with "Z". It should be noted that in the calculation of histogram value histo[0], histo[1],. . .,histo[180], we use all the pixels in an image. Although both B_{IMAGE} and Z_{IMAGE} give an indication of how severe the blocking artifacts are, their values are affected differently by the large quantization step size. As the bit rate in term of the bits per pixel drops at certain value, B_{IMAGE} starts dropping and Z_{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 quantization values. On the other hand, for some pictures with large uniform areas such as clouds, sea, or walls, etc., Z_{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,

$$DF_{\mathrm{IMAGE}} = B_{\mathrm{IMAGE}} + \beta \times B_{\mathrm{IMAGE}} \times Z_{\mathrm{IMAGE}}, \tag{12}$$

where the parameter β 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 DF_{IMAGE} is not very sensitive to the variation of β when it is within the range of 1–2.

It should also be noted that the above distortion metric is applicable to BDCT coded images without rotation. To apply DF_{IMAGE} to BDCT coded images with rotation such as the case in Fig. 6, we only need to change the angles used in Eq. 10 to be

the two maximum cells which are 90° apart. That is, we only need an extra step to find the maximum cells in the edge direction histogram before applying Eq. 10. Equations 11 and 12 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. Examples of such images are Lena, Mandrill, Peppers, and video frames from Akiyo, Coastguard, Mobile, and Garden, etc. Fig. 7 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 Laboratory for Image and Video Engineering (LIVE) (Sheikh, Wang, Cormack, Bovik, 2002). LIVE Quality Assessment Database is designed by the LIVE at The University of Texas at Austin, with collaboration of the Department of Psychology at the University of Texas at Austin. In this database, 29 high-resolution 24-bits/pixel RGB color images (typically 768 × 512) were compressed using JPEG with different compression ratios to yield a database of 204 images, 29 of which were the original (uncompressed) images. In order to get the subjective quality score of the images, each observer was shown the images randomly. Observers were asked to provide their perception of quality on a continuous linear scale that was divided into five equal regions marked with adjectives "Bad," "Poor," "Fair," "Good," and "Excellent." The scale was then converted into 1–100 linearly. The testing was done in two sessions with about half of the images in each session.

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

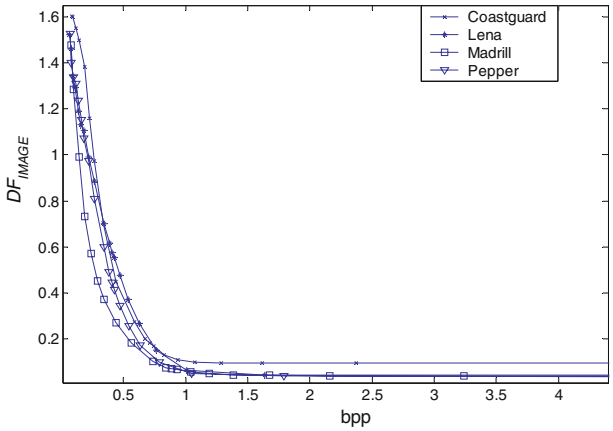

Fig. 7 DF_{IMAGE} versus bits per pixel for different images

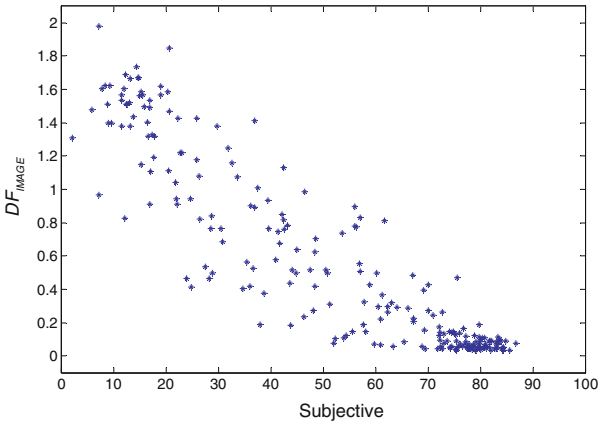

Fig. 8 Scatter plot of applying DF_{IMAGE} to the images in LIVE database

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 8 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.

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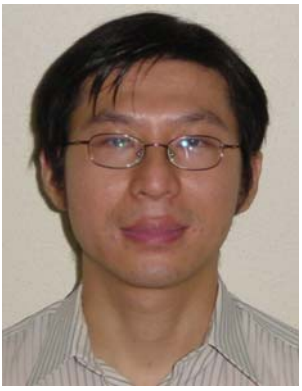

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