OBJECTIVE IMAGE QUALITY MEASURE FOR BLOCK-BASED DCT CODING

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Abstract--The block-based discrete cosine transform (DCT) coding has been widely adopted in image or video compression standards, such as JPEG and MPEG. Such type of coding will produce a noticeable artifact known as the *blocking effect* at very low bit rate applications. In the literature, there have been various postprocessing methods proposed to reduce the *blocking effect.* However, there is no suitable objective criterion evaluating the effectiveness of these various methods. This paper presents a new objective measure evaluating the postprocessing methods. The proposed measure also provides an analytical result on the underlying sources of artifacts.

I. Introduction

THE block-based discrete cosine transform (DCT) coding is among the most popular transform techniques for image and video compression. It has been adopted in compression standards, such as JPEG and MPEG. Figure 1 shows the block diagram of the block-based DCT coding algorithm. Since DCT transform and quantization steps are applied into each block, individually, quantization errors between blocks are discontinuous [6]. Such an encoding process will magnify the difference between neighboring blocks. This artifact is more obvious at very low bit rate coding and is known as *blocking effect. Blocking effect* can be observed from the Lena picture in Figure 2 that is coded at JPEG standard with quantization scale 2. Besides *blocking effect,* there are other spatial artifacts that can be found on the decoded image. But *blocking effect* is the most obvious spatial artifact of the block-based DCT coding.

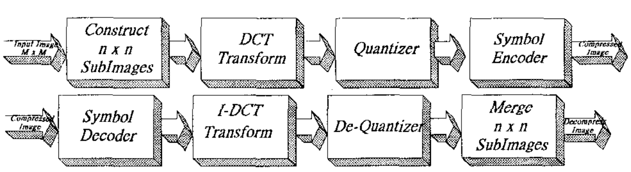

Figure 1. Block diagram of block-based DCT coding

Figure 2. Lena with blocking effect

Since *blocking effect* degrades the visual quality of DCT-compressed images seriously, there have been various postprocessing methods proposed to reduce *blocking effect* in the literature [1-12]. All the methods are designed to improve the perceptual quality by smoothing the *blocking effect* while preserving the edge information properly. If smoothing operation is applied to improper area, such as edge area, the texture and edge information of the image will be lost and the image looks like blurred. Hence, the effectiveness of one postprocessing method can be subjectively tested from the removing of *blocking effect* and the blurring of the image. But, as we known, subjective tests are time consuming and require extensive viewers. Hence, the costs of the subjective tests are too high for the researches that have not developed a good enough method. The objective tests, which give performance based on mathematical numbers, are more efficient than the subjective tests. However, there is no objective criterion that can be used to evaluate the effectiveness on the images from these postprocessing methods. The traditional pixel-based objective measures, such as PSNR or SNR, are not suitable since that these measures can even reflect a result conflicting the subjective measures [1], [3], [4]. In this paper, we propose a new objective measure BMR (*blocking-to-masking ratio*) evaluating the postprocessing methods. The measure

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evaluating the postprocessing methods. The measure provides *blocking strength* to estimate the improvement on removing *blocking effect* and *blurring strength* to estimate the degradation of the processed images from these postprocessing methods. The measure will be evaluated to have a consistent result with the subjective measure. Also, The objective measure provides an analytical result on the underlying sources of artifacts.

II. The New Objective Measure

An objective measure can be evaluated from the following three aspects. First, an objective measure should have a consistent result with the subjective measure or the perceived quality. Second, the objective measure should try to provide an analytical result that is helpful to identifying the underlying sources of artifacts. Third, the relative values of the different measures should match the degree of the psychovisual phenomenon. Unfortunately, like the field in audio and speech processing, there is always no reliable objective measure that can satisfy the above three aspects to tell the quality of the postprocessed images. This difficulty is especially severe for image or video processing because we can not yet find a good psychovisual model that can model numerically the psychovisual effects of human visual system. In the following parts, we will not present a general objective measure for all image or video processing; on the other hand, we will present an objective measure for the block-based DCT coding. We believe the dedicated approach is necessary for the finding the suitable measures. This paper will present a new objective measure based on the above three evaluation aspects.

The basic idea of our measure is that the *blocking effect* should result in an intensity varying discontinuities across block boundaries. If the coefficients are coarsely quantized, there should be a difference in the intensity slope change across the block boundaries. If this slope value is larger than original image block, some degree of *blocking effect* exists. Following this idea, we evaluate the block difference through the following four steps:

Step 1: Evaluating the block difference

Let S(i, j, m, n) be the slope between pixel(m, n) and pixel(m + 1, n) at block (i, j). Since the block size adopted in JPEG and MPEG is 8x8, the range of m and n is from 0 to 7. Then, the average slope of left boundary of block (i, j) at n ($0 \leq n \leq 7$) is

$$S_{Left}(i,j,n)=\frac{1}{2}\big(S(i-1,j,6,n)+S(i,j,0,n)\big), \tag{1}$$

and the change slope of the left block boundary is

$$SB_{Left}(i,j,n)=S(i-1,j,7,n). \tag{2}$$

Then, the blocking degree in the left side of the block is

$$\Delta L_{Left}(i,j)=\frac{1}{8}\sum_{n=0}^{7}\left|S_{Left}(i,j,n)-SB_{Left}(i,j,n)\right|. \tag{3}$$

We can similarly define the degree from the right side, the top side and the bottom side as $\Delta L_{right}(i, j)$, $\Delta L_{top}(i, j)$, and $\Delta L_{bottom}(i, j)$. The average blocking degree for the block (i, j) is then

$$\Delta L(i,j)=\frac{1}{4}(\Delta L_{Left}(i,j)+\Delta L_{Right}(i,j)+\Delta L_{Top}(i,j)+\Delta L_{Bottom}(i,j)). \tag{4}$$

Step 2 Including the perceptual effects

We define *blocking-to-masking ratio* (BMR) value to suitably include the psychovisual phenomenon as follows:

$$BMR(i,j)=50\log\frac{\Delta L(i,j)}{\Delta L_{JND}(i,j)}, \tag{5}$$

where $\Delta L_{JND}(i, j)$ is used as the threshold of the just-noticeable-difference (JND) between the adjacent blocks. The value can be evaluated according to contrast sensitivity model [13]. The model formulates the relation between contrast sensitivity threshold and background luminance. The log operation is intended to translate the contrast sensitivity curve of human visual systems into a linear scale. Finally, the scaling factor 50 is used to adjust the dynamic range of the measured value.

For this measure, if BMR(i, j) is smaller than 0, this block discontinuity must be invisible and all the corresponding blocks will be ignored.

Step 3: Separating the blocking and blurring measure

If the BMR(i, j) in the original image, labeled as OBMR(i,j), is larger than the BMR(i, j) in the processed image, labeled as PBMR(i,j), it means this processed block is blurred after processing, and we group these blocks as BR set. If OBMR(i, j) is smaller, it means the block difference of the processed image are more serious than that of the original image, we group these blocks as BK set. Hence, we define two measure values: *blocking strength* and *blurring strength* and

$$\text{blocking strength}=\frac{\sum_{block(i,j)\in BK\ set}\left|\mathrm{OBMR}(i,j)-\mathrm{PBMR}(i,j)\right|}{N_{BK}}, \tag{6}$$

$$\text{blurring strength}=\frac{\sum_{block(i,j)\in BR\ set}\left|\mathrm{OBMR}(i,j)-\mathrm{PBMR}(i,j)\right|}{N_{BR}}, \tag{7}$$

where N_{BK} is the number of blocks in the BK set and N_{BR} is the number of blocks in the BR set.

The separating of the measure into the *blocking effect* and the blurring effect can provide simultaneously objective test for the two effects arising from the postprocessing, and hence has more analytical results.

Step 4. Constructing the Single BMR value

At the final step, we combine *blocking strength* value and *blurring strength* value into one single BMR value. The single BMR value can be evaluated by the summing of the two strength values:

$$\text{BMR} = \textit{blocking strength} + \textit{blurring strength}\,. \quad (8)$$

The BMR value can be looked as an indicator for the whole image perceived quality.

We also construct a reference table (Table 1) based on this measure to test the image quality on the blocking effect and blurring effect. The table classifies the image quality into six groups: *blocky, slightly blocky, smooth, slightly blurred, oversmooth,* and *Inferior*. Each image is grouped according to the image *blocking strength* value and *blocking strength* value. If the image quality belongs to *blocky*, blocking effect should be obviously discoverable in the image. If the image quality belongs to *slightly blocky*, blocking effect should not be obvious and the image is still acceptably clear. If the image quality belongs to *smooth*, blocking effect is removed well and the image quality is still acceptably clear. If the image quality belongs to *slightly blurred*, the image is slightly blurred, but the image is still acceptably clear. If the image quality belongs to *oversmooth, blurring effect* is serious but *blocking effect* is not obvious. If the image quality falls in *Inferior* degree, the image quality is both poor in blocking effect and in blurring effect. Following this classification, we can easily determine the image quality.

III. Experiment Results

We have evaluated the new criterion through three post-processing methods: space-variant low-pass filtering [3], low-pass filtering, and convex-projection method [4]. The main objective of these methods is to remove blocking effect while preserve edge information properly. We introduce these methods briefly to help understanding the experiment.

In the space-variant lowpass filtering methods, the whole image is divided into edge and nonedge areas. To preserve the edge information, lowpass filtering will be only applied on nonedge areas to reduce blocking effect. In different areas, different low-pass filters are applied.

In the convex projection (CP) methods, convex-projection theory [14] is applied on the decompressed image to restore the original image. The theory relies on the prior information of the original image, such as smoothing and edge information on removing blocking effect, to construct appropriate convex sets. Then, the decompressed image is processed by iterative projection operations to obtain the restored image [14].

Table 1.Blocking effect rating scale

Description	Rating	Blocking strength	Blurring strength
Blocky	Poor	> 6	< 9
Slightly blocky	Acceptable	> 4 & < 6	< 9
Smooth	Good	< 4	< 7
Slightly blurred	Acceptable	< 4	< 9 & > 7
Oversmooth	Poor	< 6	> 9
Inferior	Very Poor	> 6	> 9

The experiment results are summarized in Table 2 and Table 3. In these tables, "Q1" denotes quantization by the quantization table of JPEG standard; "Q15" denotes quantization by the standard table multiplied by the factor 1.5; "Q2" denotes quantization by the standard table multiplied by the factor 2. We can see from Table 2 that lowpass filtering is the best method to reduce blocking effect, but, by comparing the decompressed image (Figure 4) and the lowpass filtered image (Figure 5, 3 x 3 equal-weight average filter), we can know that it also blurs the image seriously. The corresponding PSNR and SNR value, however, can not reflect these phenomena. In our measure, all the processed images from lowpass filtering have blocking-strength values smaller than others, but their blurring-strength values are all larger than others. In the implementation of the space-variant lowpass filtering [3], the flat areas are processed by lowpass filtering and edge areas are left unprocessed. We can see the processed image in Figure 6 that the flat areas are well smoothed, but the texture or edge areas are still acceptably clear. In the corresponding PSNR and SNR, we only know the quality of the processed images should be within that of the unprocessed images and that of the lowpass filtered images. In our measure, we can find the blocking-strength values and the blurring-strength values of the processed images are all within the values of the unprocessed image and the values of the low-pass filtered.

As to the CP method, we have implemented this method according to the algorithm in [4]. The evaluation results of all the processed images at each iteration are summarized in Table 3. Figures 7 - 9 show the processed images at iterations 1, 3, and 10. From these images, we can see the difference between each images at each iteration are small, but in some texture areas, such as hat area, we find the smoothing effect disappears gradually and blocking effect becomes more apparently as the iteration number increases. This is due to the fact that smoothing filter is only applied at the first step and, in the iterations, there is no any operation to keep smooth property. In the measures of Table 3, we find that the PSNR or SNR values are stable as iteration number increases. Hence, these two measures can not reveal the visual quality of CP-processed images. However, in the proposed BMR measure, *blocking strength* approximately increases and *blurring strength* approximately decreases with the iteration number, which matches the subjective evaluation of these images.

IV. Conclusion

This paper has proposed a new objective measure for block-based DCT coding. The measure gives an analytical result for both the blocking effect and the blurring effect of the images due to postprocessing. This measure has considered the perceptual effect by including the contrast sensitivity model of human vision system, and has been evaluated to have a consistent result with the subjective measure.

Table 2. LP filter (window size 3 x 3, coefficients are all 0.111). SVLP filter (use [3]).

Postprocessing	QUANT.	PSNR (db)	SNR (db)	(blocking, blurring)	BMR
None	LenaQ1	31.6713	26.7635	(4.8693, 5.8357)	10.705
None	LenaQ15	30.4625	25.5547	(5.8718, 6.5273)	12.3991
None	LenaQ2	29.5897	24.6819	(6.1190, 7.0874)	13.2064
LP filter	LenaQ1	27.9823	23.0745	(2.5743, 11.5878)	14.1621
LP filter	LenaQ15	27.6146	22.7068	(2.4676, 11.6082)	14.0758
LP filter	LenaQ2	27.2943	22.3865	(2.5552, 11.9945)	14.5497
SVLP filter	LenaQ1	29.5506	24.6428	(4.5467, 6.8038)	11.3505
SVLP filter	LenaQ15	28.8363	23.9285	(5.3036, 7.4010)	12.7046
SVLP filter	LenaQ2	28.2811	23.3733	(5.6993, 7.7892)	13.4885

Table 3. Convex-Projection Method ([4]). Processed image is LenaQ15

Iteration	PSNR(dB)	SNR(dB)	(blocking, blurring)	BMR
1	30.3183	25.4846	(4.5534, 7.1460)	11.6994
2	30.3217	25.4881	(4.5676, 7.3213)	11.8889
3	30.3212	25.4876	(4.6986, 7.1921)	11.8907
4	30.3210	25.4874	(4.8180, 7.0734)	11.8914
5	30.3215	25.4878	(5.0040, 7.0683)	12.0723
6	30.3208	25.4872	(4.7990, 7.0898)	11.8888
7	30.3196	25.4860	(4.9542, 7.0459)	12.0001
8	30.3199	25.4863	(5.0348, 7.0319)	12.0667
9	30.3171	25.4834	(5.0429, 6.9947)	12.0376
10	30.3168	25.4832	(5.0595, 6.9968)	12.0563

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Figure 3. Original Lena

Figure 4. LenaQ15

Figure 5. Low-pass filtering applied in LenaQ15 (3 x 3 equal-weight average filter)

Figure 6. SVLP filtering applied in Lena Q15

Figure 7. CP method applied in LenaQ15 at iteration 1

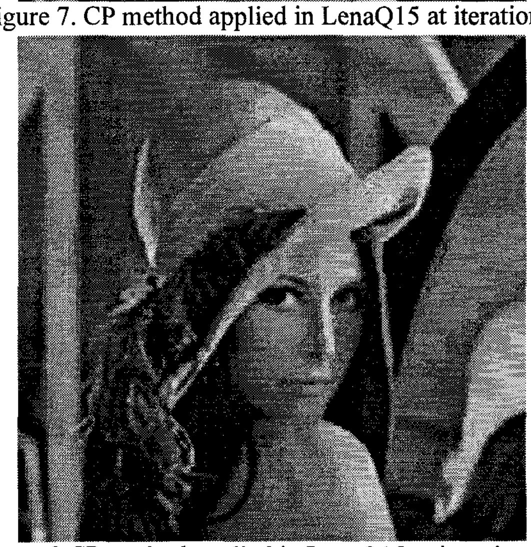
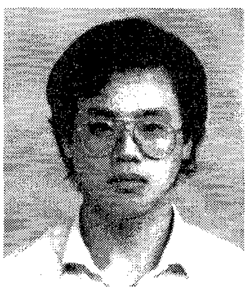


Figure 8.CP method applied in LenaQ15 at iteration = 3

Figure 9. CP method applied in LenaQ15 at iteration = 10

Biographies



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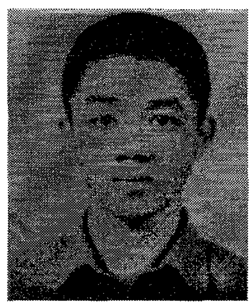

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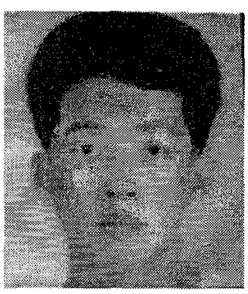

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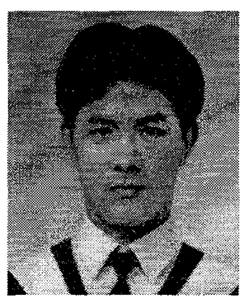

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