Improve JPEG Image Compression by using Adaptive Downsampling and Quantization Modes at Low Bit Rates

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Abstract: We can improve image compression by downsampling the image prior to encoding process and estimated the missing portion after decoding at low bit rates. This paper presents a new algorithm in which , based on the adaptive decision of appropriate downsampling ratios and quantization steps we will achieve high quality of coding by consideration of local visual significance at low bit rates and at high bit rates it acts as a conventional JPEG compression. The full resolution image can be restored from the DCT coefficients of the downsampled pixels at decoder. The proposed algorithm significantly raises the critical bit rate to approximately 1.2 bpp, from 0.15-0.41 bpp in the existing downsample-prior-to-JPEG schemes and, therefore, outperforms the standard JPEG method in a much wider bit-rate scope. The experiments have demonstrated better PSNR improvement over the existing techniques before the critical bit rate. In addition, the adaptive mode decision not only makes the critical bit rate less image-independent, but also automates the switching coders in variable bit-rate applications, since the algorithm turns to the standard JPEG method whenever it is necessary at higher bit rates.

Index Terms: Downsampling, image compression, low bit rate, mode decision, perceptual visual quality, spatial variation

I. INTRODUCTION

IN INTERNET and mobile multimedia applications, visual signals usually need to be coded at low bit rates. The conventional image compression methods (e.g., JPEG and JPEG2000 standards) attempt to allocate the available bits for image. When the compression ratio increases, the bits per pixel (bpp) decreases as a result of the use of bigger quantization step sizes, and the resultant coded picture quality deteriorates. At low bit rates (e.g., below 0.5 bpp), these standard schemes usually cause very severe blockiness and other coding artifacts coefficient.

It is well known that high spatial correlation exists among neighboring pixels in a natural image; in fact, most images are obtained via interpolation from sparse pixel data yielded by single-sensor camera. Therefore, some of the pixels in an image may be omitted (i.e., the image is downsampled) before compression and the follow-on storage/transmission, and at the decoding end they can be restored from the available data (e.g., interpolated by the neighboring pixels). Research has shown that downsampling prior to encoding and upsampling after decoding can improve the quality of coded image at low bit rates [1]-[3] in comparison with the standard JPEG method at a low bit rate. Downsampling is not good for high bit-rate coding (on which we will elaborate in Section II-A). However, in the situations where the allowed bits cannot represent all pixel information sufficiently anyhow, overall coded picture quality may be improved if the scarce bandwidth is used for better coding of sparse visual data while the other data are restored at the de-coding end. We use the term critical bit rate to denote the maximum bit rate for a downsampling-based scheme to outperform the traditional whole-image compression; the higher the, the wider the range of bit rates in which the scheme can improve image compression.

In [1], Zeng and Venetsanopoulos used a 2×2 average operator for spatial decimation before JPEG compression; at decoding, they used a replication filter and then a 5×5 Gaussian filter to restore the whole image. Bruckstein et al. exploited the theoretical model of downsampling and compared it with experimental results. In Tsaig et al.'s work, image dependent decimation and interpolation filters are derived for Bruck-stein et al.'s method and the resultant filter parameters are sent to the decoder for better restoration. In the existing schemes, the downsampling ratio is preset by users; the critical bit rate is low and image dependent, and an encoding process has to be switched between a downsampling scheme and the traditional scheme, in a variable bit-rate (VBR) application for different images, if good coding quality is sought.

In low bit-rate coding, whether and how to downsample an image should be determined by the contents of visual signal itself, so that the scarce bits can be used to achieve the best coding quality. In the light of this idea, we propose the strategies to adaptively decide the appropriate downsampling ratio/direction and quantization step for encoding every macro block in an image, based upon the local visual significance of the signal. If possible, downsampling should be avoided along the direction of high spatial variations, which signal the existence of edges and other image features with great impact on perceptual visual quality. As expected, the proposed scheme is capable of outperforming the existing downsampling methods, in terms of coding quality and the critical bit rate. Furthermore, the above mentioned coder switching becomes automatic and adaptive to the actual of the image under processing. In this work, we also estimate the full-resolution DCT coefficients from the available DCT coefficients resulting from the downsampled sub image, without the need of a spatial interpolation stage in the decoder.

In Section II of this paper, the impacts of downsampling are first analyzed, and the strategies are discussed for the adaptive decision on downsampling and quantization modes (QMs), in order to reduce coding and estimation distortion. Section III presents the estimation of the full-resolution DCT coefficients from the DCT coefficients of the downsampled sub image. Section IV demonstrates the experimental results of the proposed scheme, in comparison with the existing downsampling methods, while the last section concludes the paper.

II.ADAPTIVE DETERMINATION OF DOWNSAMPLING AND QUANTIZATION MODES

Let I and $I^{t,l}$ denote an original (full resolution) image and its downsampled sub image, with t and l being zero or positive integers (i.e.,t,l≥0) representing the downsampling factors in horizontal and vertical directions, respectively. When t (or l)=0, there is no downsampling in horizontal (or vertical) direction; when t (or l)=1 , there is 1/2 downsampling in horizontal (or vertical) direction; when t =l=1, there is 1/2 downsampling in both horizontal and vertical directions, and the total downsampling ration is 1/4; and so on. We use $\tilde{I}^{t,l}$ denote the discarded portion of I after downsampling, so $\tilde{I}^{t,l} = I - I^{t,l}$. Fig. 1 shows an example of downsampling when t=1 and l=0.

A. Downsampling Process and Its Impacts

The coding distortion of a conventional DCT-based compression (e.g., JPEG) for image can be represented as

$$E(I)=E_c(I)= E_c(I^{t,l})+ E_c(\tilde{I}^{t,l}) \quad \text{----------- (1)}$$

Where $E_c(.)$ is a distortion measure that accounts for DCT rounding error and quantization error for the portion of image. With downsampling, we code $I^{t,l}$ at a same bit rate and estimate $\tilde{I}^{t,l}$ at the decoding stage, and the resultant overall distortion is

$$E^{t,l}(I)=E'_c(I^{t,l})+E_p(\tilde{I}^{t,l}) \quad \text{------------(2)}$$

Where $E'_c(I^{t,l})$ denotes a distortion measure of DCT rounding and quantization for $I^{t,l}$, and $E_p(\tilde{I}^{t,l})$ denotes an estimation distortion measure for the reconstruction of $\tilde{I}^{t,l}$.

The distortion measures E_c, E'_c, E_p and can be obtained with a mean-square error (MSE)-type metric or a perceptual metric.

For a downsampling scheme to outperform the conventional compression method, the following must be satisfied:

$$E^{t,l}(I)< E(I) \quad \text{---------(3a)}$$

or equivalently

$$E_c(I^{t,l})- E'_c(I^{t,l}) > E_p(\tilde{I}^{t,l})- E_c(\tilde{I}^{t,l}) \quad \text{---(3b)}$$

Fig. 1 illustrates the pixel positions before and after a downsampling process in an image. As can be seen, downsampling results in the reduction of geographic distance between pixels, and, therefore, the increase of spatial frequencies. Regardless of the difficulty in coding caused by such frequency increase, downsampling still results in a smaller $E'_c(I^{t,l})$ because more bits are now available for coding alone, therefore $E_c(I^{t,l})- E'_c(I^{t,l}) >0$ -----(4)

Inequality (3b) cannot be held for high bit rates because the reduction of $E'_c(I^{t,l})$ is not big enough to offset the increase of $E_p(\tilde{I}^{t,l})$ in high quality compression. Since $E_c(I^{t,l})$ and $E_c(\tilde{I}^{t,l})$ are constant with the given bit rate for an image, a downsampling scheme needs to reduce its coding distortion $E'_c(I^{t,l})$ and estimation distortion $E_p(\tilde{I}^{t,l})$ as far as possible. The critical bit rate B is the maximum bit rate for Inequality (3) to be held. $E'_c(I^{t,l})$ and $E_p(\tilde{I}^{t,l})$ are closely related to spatial visual significance in the image. When the spatial variation is mild along one direction in a region of the original image (i.e., the visual significance is low in that direction), downsampling is an appropriate way to achieve low rate compression, because it results in small coding distortion $E'_c(I^{t,l})$ and allows reasonable estimation[with small $E_p(\tilde{I}^{t,l})$]. When the spatial

variation is significant along one direction, there exist more visual details, such as edges, which are of primary importance in visual perception. Under this circumstance, downsampling has to be avoided,
without incurring loss of meaningful spatial variations (governing by Nyquist theorem) or making them difficult to be represented adequately after the quantization step later on [both yielding big $E_c(I^{t,l})$]; besides, pixels in image regions with big spatial variations cannot be restored sufficiently at the decoding stage[thus, $E_p(I^{t,l})$ is big]

B. Mode Decision

A straightforward approach for the downsampling decision is to evaluate the gradients or high-frequency DCT components along

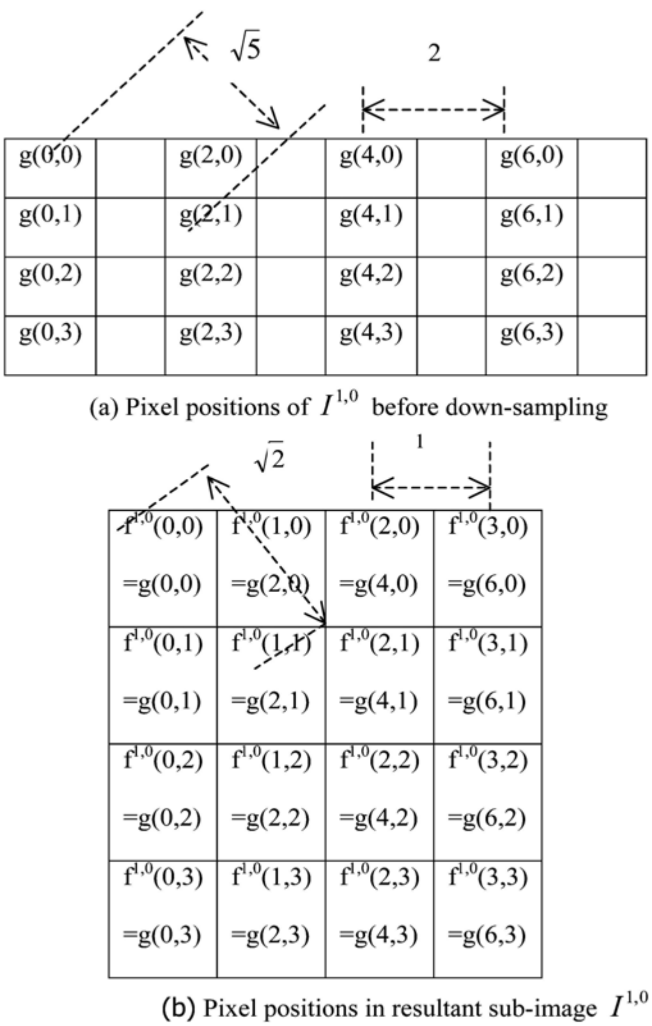

Fig.1 Illustration of geographic distance changes with 1/2 downsampling in the horizontal direction (t=1, l=0).

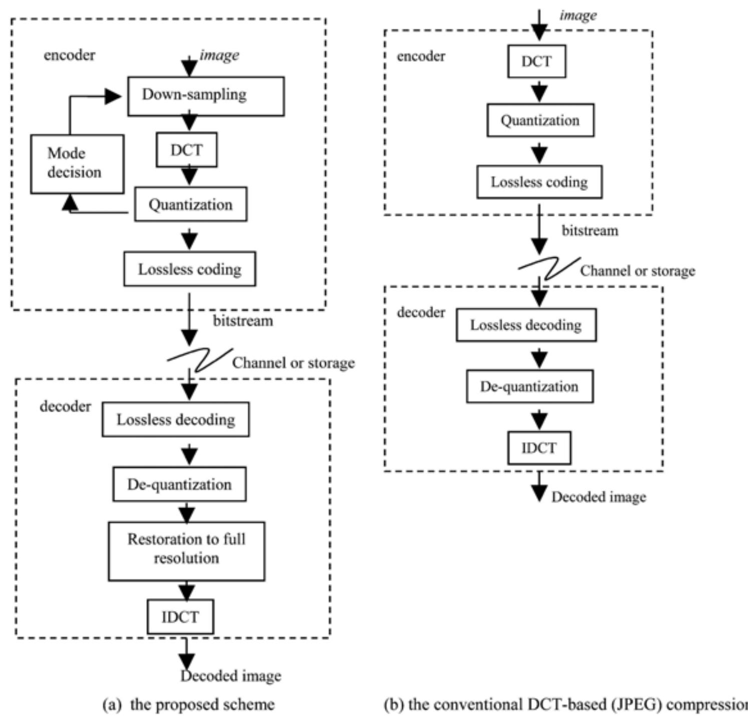

Fig.2.Block diagram comparison of the proposed scheme and the conventional DCT-based (JPEG) compression: (a) the proposed scheme; (b) the conventional DCT-based (JPEG) compression

DSM	Description
DSM_0	one 16x16 macroblock to four 8x8 blocks (no downsizing; $t=l=0$)
DSM_1	one 16x16 macroblock to two 8x8 blocks in horizontal direction (1/2 down-sampling (1-D) along vertical direction; $t=0$ and $l=1$)
DSM_2	one 16x16 macroblock divided to two 8x8 blocks in vertical direction (1/2 down-sampling (1-D) along horizontal direction; $t=1$ and $l=0$)
DSM_3	one16x16 macroblock to one 8x8 block (1/4 down-sampling (2-D) along both vertical & horizontal directions; $t=l=1$)

TABLE I
DOWNSAMPLING MODES

QM	Description
QM_0	QP/4
QM_1	QP/2
QM_2	3*QP/4
QM_3	QP

TABLE II
QUANTIZATION MODES

each direction. In this section, we propose an adaptive and integrated algorithm, to determine both the appropriate downsampling mode (DSM) and the appropriate quantization step for each region in the image. Fig. 2 shows the block diagram comparison of the proposed algorithm and the conventional DCT-based (JPEG) compression. The current implementation of the work is with downsampling ratio varying from 1/4 to 1 (i.e.,0≤t,l≤1), and, obviously, this is the

most useful situation. Table I lists four possible DSMs for a 16×16 macroblock, with different downsampling ratios and directions. First, DSM_0 is performed (i.e., four 8×8 DCTs, without downsampling) with the quantization parameter QP determined in the same way as in the JPEG compression under a bit-rate constraint. The proposed algorithm aims at finding an alternative DSM (i.e., DSM_1, DSM_2, or DSM_3) in the macroblock, to achieve better coding quality than bit rate constraint. In the current stage of this study, the target number of bits to be allocated for a macroblock is the same number of bits used in

TABLE III

COMPARISION OF THE CRITICAL BIT RATE (IN BPP) FOR DIFERENT ALGORITHMS.

Image (size)	Zeng & Venetsanopoulos [8], with ¼ down-sampling	Bruckstein, et. al. [9] down-sampling			the proposed algorithm with variable down-sampling (¼ to 1)
		9/16	1/4	1/8	
Lena (512x512)	0.29	--	--	--	
Lena (256x256)	--	0.39	0.29	0.20	
Barbara (512x512)	0.26	0.28	0.21	0.17	~ 1.2
Boats (512x512)	0.27	0.35	0.24	0.15	
Goldhill (512x512)	--	0.41	0.23	0.16	

the full resolution JPEG compression. With DSM_1, DSM_2, and DSM_3, the quantization parameter can be reduced to code the DCT coefficients for the downsampled pixels more accurately. Because the downsampling ratio varies from 1/4 to 1, four QMs being used are set as Table II. We calculate the coding distortion in terms of MSE $e_{0,3}$ for the macroblock with DSM_0 and QM_3 (i.e., the standard JPEG compression)[4], and count the corresponding

number of nonzero quantized DCT coefficients $NZC_{0,3}$ as the reference for searching the best DSM and QM later on. The notation $e_{min-so-far}$ is used to keep track of the minimum MSE ever achieved in the course of searching, and its initial value is $e_{0,3}$.

We evaluate DSM_1, DSM_2, and DSM_3, in turn.QM_0, QM_1, QM_2 and QM_3 are tried in sequence for each DSM_n, until a certain QM_p satisfies

$$NZC_{n,p} \leq NZC_{0,3} \text{ -------------5(a)}$$

and

$$e_{n,p} < e_{min-so-far} \text{ --------------5(b)}$$

Where $e_{n,p}$ evaluates the MSE of the restored full-resolution image after dequantization, against the original image I. Inequality (5) is used to choose the mode with lower MSE but with no increase of nonzero quantized DCT coefficients. Once (5) is met, the process for DSM_n is terminated[1] and $e_{min-so-far}$ is updated as $e_{n,p}$. The same process repeats for DSM_{n+1}.The combination of DSM and QM corresponding to the final $e_{min-so-far}$ (noted as e_{min}) is used to compress the image. DSM_1, DSM_2, and DSM_3 represent downsampling along the horizontal direction, the vertical direction, and both of the directions. If the spatial variation along one (or both) of the directions is small, the corresponding DSM is likely to be chosen in the procedures above. If $e_{min} = e_{0,3}$ after the mode search, the standard JPEG compression is used to compress the macroblock. So, as a bonus for the proposed algorithm, the difficulty of detection of the critical bit rate B is avoided and the switching of coders (between the standard JPEG coder and a downsampling-based coder) is automated for VBR applications, since the algorithm results in the standard JPEG compression if all the other DSMs and QMs fail to yield better coding picture quality.

III. ESTIMATION OF FULL-RESOLUTION DCT COEFFICIENTS

Although the adaptive mode decision described in the last section may be used in

conjunction with spatial interpolation at the decoding end, in this work, we restore the

full-resolution image from the full-resolution DCT coefficients from the downsampled sub image $I^{t,l}$, so the spatial interpolation required otherwise is avoided and the full-resolution image is obtained directly with IDCT.

Since two-dimensional (2-D) DCT can be realized by two one-dimensional (1-D) DCTs, the case of 1-D DCT is first considered below. For a 1-D original signal g(r) where r is the pixel position index, N pixels after downsampling the original signal with downsampling factor t can be represented as

$f^{t}(n)=g(2^{t}n)$---------(6)

Where $0 \le n \le N-1$.

The N-point DCT of $f^{t}(n)$ is

$$F^{t}(k)=\sum_{n=0}^{N-1} a(k) * \cos(\pi k/N(n+0.5)) * f^{t}(n) \quad \text{---(7)}$$

Where a(k) denotes N-point DCT

Normalization parameter

$a(k)=\sqrt{1/N}$,k=0

$\sqrt{2/N}$, otherwise.

Let $G^{t}(k)$ denote the 2^{t}N-point DCT of g(r); obviously, $G^{0}(k)=F^{0}(k)$; and when t=1, the 2N-point DCT of g(r) is in (8), shown below where $0 \le k \le 2N-1$,and $\epsilon^{1}(k)=1/\sqrt{2}$

$$\sum_{n=0}^{N-1} a(k)*[g(2n+1)-g(2n)]*\cos(3.14k/2N(2n+1+1/2))$$

-----------------(9). With the substitution of (6)

$$G^{1}(k)=\sqrt{2} * \sum a(k)*f^{1}(n)*\cos(3.14*k/N(n+1/2))*\cos(3.14*k/2^{2}N) + \epsilon^{1}(k)$$ ------ (10)

For $0 \le k \le N-1$, With the substitution of (7), We have $G^{1}(k)=\sqrt{2} * F^{1}(k)*\cos(3.14*k/2^{2}N)+\epsilon^{1}(k)$ is a term determined by the difference of every pair of neighboring pixels in the original image, and is expected to be small due to the high spatial correlation in natural images; $G^{1}(k)$, when $N \le k \le 2N-1$ represents the higher frequency components and can be ignored in low bit rates. Therefore, an approximation of $G^{1}(k)$ can be made for low bit-rate coding

$$G_{a}^{1}(k)=\begin{cases}\sqrt{2} * F^{1}(k)*\cos(3.14*k/2^{2}N), & \text{if } 0 \le k \le N-1 \\ 0, & \text{else}\end{cases}$$

Following the similar derivation, we can have the general formula for $G^{t}(k)$ when t>1

$$G_{a}^{t}(k)=\begin{cases}2^{(t/2)} F^{t}(k)\prod_{p=1}^{t}\cos(3.14*k/2^{(p+1)}N), & \text{if } 0 \le k \le N-1 \\ 0, & \text{else}\end{cases}$$

Where $0 \le k \le 2^{t}N-1$ The above results can be further extended to the 2-D situation, in which an block of pixels after downsampling the original signal g(r,s),where r and s are pixel position indices, is represented as $f^{t,l}(n,m)=g(2^{t}n,2^{l}m)$ where $0 \le n,m \le N-1$. The full-resolution 2-D DCT coefficients $G^{t,l}(k,j)$ can be estimated for the N×N DCT coefficients $F^{t,l}(k,j)$ resulting from $I^{t,l}$ (14), shown at the bottom of the page, where $0 \le k \le 2^{t}N-1$ and $0 \le j \le 2^{l}N-1$. At the decoding end, the $2^{t}N \times 2^{l}N$ IDCT of $G_{a}^{t,l}(k,j)$ estimates the full-resolution image I , and the spatial interpolation (as in [8] and [9]) is not needed. In this study, four cases have been used (i.e.,l=l=0;t=0,l=1;t=1,l=0;and t=l=1).

$$\begin{aligned}
G^{1}(k) &= \frac{1}{\sqrt{2}}\sum_{r=0}^{2N-1}\alpha(k)*\cos\left(\frac{\pi k}{2N}\left(n+\frac{1}{2}\right)\right)*g(r) \\
&= \frac{1}{\sqrt{2}}\sum_{n=0}^{N-1}\alpha(k)*\left[\cos\left(\frac{\pi k}{2N}\left(2n+\frac{1}{2}\right)\right)*g(2n)+\cos\left(\frac{\pi k}{2N}\left(2n+1+\frac{1}{2}\right)\right)*g(2n+1)\right] \\
&= \frac{1}{\sqrt{2}}\sum_{n=0}^{N-1}\alpha(k)*g(2n)*\left[\cos\left(\frac{\pi k}{2N}\left(2n+\frac{1}{2}\right)\right)+\cos\left(\frac{\pi k}{2N}\left(2n+1+\frac{1}{2}\right)\right)\right] \\
&\quad + \frac{1}{\sqrt{2}}\sum_{n=0}^{N-1}\alpha(k)*[g(2n+1)-g(2n)]*\cos\left(\frac{\pi k}{2N}\left(2n+1+\frac{1}{2}\right)\right) \\
&= \sqrt{2}\sum_{n=0}^{N-1}\alpha(k)*g(2n)*\cos\left(\frac{\pi k}{N}\left(n+\frac{1}{2}\right)\right)*\cos\left(\frac{\pi k}{2^{2}N}\right)+\epsilon^{1}(k)
\end{aligned}$$

$$G_{a}^{t,l}(k,j) = \begin{cases}2^{(t+l/2)}F^{t,l(k,j)}\prod_{p=1}^{t}\cos(k*3.14/2^{p+1}N) * \prod_{q=1}^{l}\cos(j*3.14/2^{q+1}N) & \text{if } 0 \le k,j \le N-1 \quad \text{---(14)} \\ 0, & \text{else}\end{cases}$$

IV. RESULTS OF EXPERIMENTS

The following standard gray-level images are used for the experiments and the comparison with the relevant existing downsampling-based methods [8] and [9]: *Lena* (512× 512), *Lena* (256 ×256), *Barbara* (512× 512), *Boats* (512 ×512), and *Goldhill* (512× 512). We used two-point averaging for 1-D downsampling (for DSM_1, DSM_2), and four-point averaging for 2-D downsampling (for DSM_3). The averaging operation also alleviates the aliasing effect. In the experimental results to be presented below, the additional overheads (i.e., 4 bits per macroblock) for representing the DSM and the QM are included in the bpp calculation for the proposed method. Table III first lists the values of the *critical bit rate* derived from Zeng and Venetsanopoulos' result [1] and Bruckstein *et al.*'s result [2]: ranges from 0.15 to 0.41 bpp for these two methods, depending on the downsampling ratio (t=l in the two methods) and the image contents. The last column of Table III shows that the measured value B for the proposed algorithm is about 1.2 bpp for all four images, and this is a significant improvement over the two other methods.

Fig.3 compares PSNR versus bit rate for the standard JPEG method and the proposed algorithm, with the four 512×512 images. The proposed algorithm not only results in a significantly higher B (i.e., it outperforms the standard JPEG method in a much wider scope of bit rates), but also yields a largely image-independent B (the downsampling ratio is no longer a parameter since it is adaptively determined); these two aspects of improvement are attributed to the adaptive decision process for DSMs and QMs in the proposed algorithm.

As shown in Fig. 3, the PSNR improvement of the proposed algorithm over the standard JPEG method can be up to 1.9 to 3.4 dB at very low bit rates (lower than 0.2 bpp), for the images used, while with a bit rate between 0.2 and 1.2 bpp (the *critical bit rate B*); the proposed algorithm still yields considerable PSNR gain.

Fig.4 shows an example at around 0.290 bpp with image Boats (512×512); the proposed algorithm [Fig. 4(b)] has a PSNR gain of 0.82 dB and obvious perceptual quality improvement (especially in the cloud and sky regions) over the standard JPEG method [Fig. 4(a)].The statistics of the mode decisions made are quite consistent over different images, and Fig. 5 shows the average number of macroblocks over the four 512×512 images for each DSM and QM with different bit rates. obviously, DSM_1,DSM_2 ,and DSM_3,and QM_0 and QM_1 dominate in lower bit rates, while DSM_0 and QM_3(corresponding standard JPEG compression) dominate in the lower bit rates, with a higher bit rate, nearly all macroblocks are with QM_3 and DSM_0, and this means that the proposed algorithm approaches the standard JPEG compression when the bit rate is high; therefore, the coder switching is automated for variable bit rates and different images, and the transition is graceful.

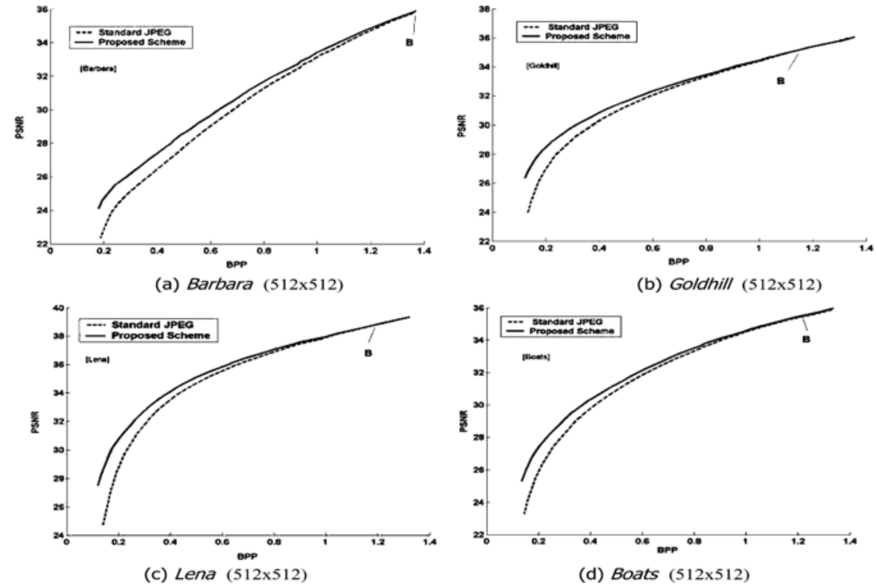

Fig. 3. PSNR comparison at different bit rates for the standard JPEG and the proposed algorithm

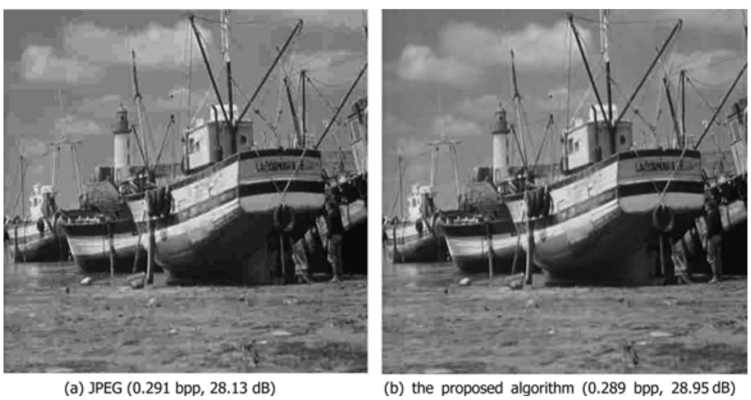

Fig. 4. Image Boats (512 × 512) coded with the standard JPEG and the proposed algorithm.

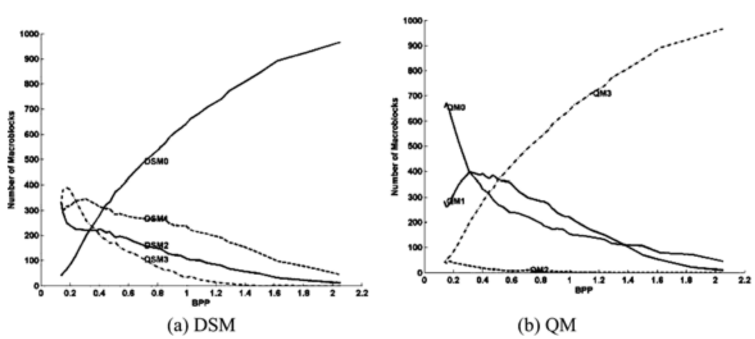

Fig. 5. Average number of macroblocks for each DSM or QM, with the four images of size 512 × 512, at different bit rates

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V. CONCLUSION

This paper has been devoted to improve image compression at low bit rates with spatial downsampling. Based upon the idea that downsampling is better to be performed according to local visual significance, we have proposed an adaptive decision process for appropriate downsampling and QMs. In the current implementation, the downsampling ratio is automatically adjusted from 1/4 to 1, according to local image contents. Different modes are chosen for different regions of an image, to achieve the highest coding quality under the same bit-rate constraint.

The proposed algorithm significantly raises the *critical bit rate* to approximately 1.2 bpp, in comparison with 0.15 to 0.41 bpp in the other downsample-prior-to-JPEG schemes, and, therefore, is capable of outperforming the standard JPEG method in a much wider bit-rate scope. The adaptive mode decision not only makes the *critical bit rate* largely image independent, but also automates the coder switching in VBR applications since the proposed algorithm turns to the standard JPEG compression whenever it is necessary. The experiments have demonstrated obvious PSNR improvement (e.g., a gain of up to 1.9 to 3.4 dB at a bit rate of <0.2 bpp) over the other schemes before the *critical bit rate*. Therefore, the proposed technique achieves significantly better-than-JPEG coding quality (in both objective and perceptual terms) with a wider scope in low bit rates, and guarantees the not-worse-than-JPEG performance at any bit rates.

Although the adaptive mode decision itself may be used in conjunction with spatial interpolation at the decoding end, we have devised a method to restore the full-resolution image from the DCT coefficients of the downsampled sub image; thus, the spatial interpolation required otherwise is avoided, and the full-resolution image is restored directly with IDCT. The current implementation is with downsampling ratio adaptively varying from 1/4 to 1. However, the proposed strategies can be utilized to allow other downsampling ratios when there is a need.

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