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ESTIMATION OF ACCESSIBLE QUALITY IN NOISY IMAGE COMPRESSION

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ABSTRACT

A task of lossy compression of noisy images providing accessible quality is considered. By accessible quality we mean minimal distortions of a compressed image with respect to the corresponding noise-free image that are observed for the case of optimal operation point (OOP). The ways of reaching OOP for noisy images are discussed. It is shown that this can be done in automatic mode with appropriate accuracy. Investigations are performed for efficient DCT-based AGU coder for a set of test images. We also demonstrate that the proposed approach can be applied to automatic selection of compression ratio for lossy compression of noise-free images.

1. INTRODUCTION

Image compression has been an area of intensive research in recent two decades [1]. Compression of noisy images is of particular interest for such applications as medical imaging [2], remote sensing data coding [3,4], monitoring systems [5,6], etc. Compression of images obtained by digital cameras operating in poor illumination conditions is one more application for which original images can not be considered to be noise-free.

Note that a lossless compression of noisy images for the considered applications is commonly useless. The achievable compression ratio (CR) is usually only slightly larger than unity. Thus, lossy techniques comprise a basic tool in noisy image compression.

Lossy compression being applied to noisy images has several peculiarities. First, suppose that compression of an image is performed not with the basic purpose to further transfer it via communication channel with a limited bandwidth, but with the purpose of storing (archiving) an image keeping in mind that later it will be decompressed, visualized and/or interpreted. Such a situation is typical, e.g., for ultrasound medical images, multi-temporal remote sensing data, etc. Then the primary goal is to provide an image quality appropriate for its analysis (interpreting) in future rather than to ensure maximal or desirable compression ratio (CR) (in the later case, a useful information can be inevitably lost in decompressed data).

Second, a quality of compressed noisy image is worth characterizing not with respect to the original one but with respect to a noise-free one. Because of this, in performance analysis of techniques for noisy image lossy compression people commonly use the corresponding quantitative criteria [2,5-10]. The most often used criterion derived in this manner is the peak signal-to-noise ratio (*PSNR*). Let us further denote it as $PSNR_{nf}$. But $PSNR_{nf}$ can be calculated only for test images to which noise is artificially added. At the same time, for real life noisy images, *PSNR* for compressed data can be calculated only with respect to original noisy images (such *PSNR* is below denoted as $PSNR_{or}$).

Third, alongside with decreasing a compressed image size compared to the original image,lossy compression performs noise reduction [2-9]. This is a useful phenomenon since noise in images does not contain any valuable information about sensed terrain or imaged scene. However, simultaneously with a noise reduction, lossy compression introduces distortions of useful information contained in original images. In [5,8,10] it has been demonstrated that there exists such a point of dependence of $PSNR_{nf}$ on CR (bpp) for which $PSNR_{nf}$ is maximal (this CR or bpp is called “the optimal operation point”). Some details proving this are given in Section 2.

In practice, it is reasonable to perform lossy compression of noisy images with CR corresponding to OOP in order to provide accessible quality of compressed images. The procedure of OOP determination is to be simple and automatic.

Note that OOP value depends upon noise and image characteristics. In [5,8], recommendations how to reach OOP have not been given. An automatic procedure for accessing OOP has been proposed in our paper [10] (see Section 2 for some details). However, this procedure requires several iterations to compress and decompress an image and, generally speaking, it can be applied to any kind of coder. Below, in Section 3, we show how to access OOP for transform based coders, e.g. AGU coder [11], without any iteration. The corresponding study is performed for the five test images corrupted by an additive Gaussian noise with three different variances.

Moreover, in Section 4 we demonstrate for the same set of test images that the proposed automatic procedure can be used for noise-free image compression. Thus, the proposed procedure is universal in the sense that it allows one to find OOP when compressing noisy images and produces an appropriate quality for a noise-free image compression.

2. PECULIARITIES OF NOISY IMAGE COMPRESSION

Suppose we have a noise-free test image $\{I_{ij}\}$, the same image $\{I_{ij}^n\}$ corrupted by an additive Gaussian noise with zero mean and variance σ^2 and the image $\{I_{ij}^d\}$ after compressing and decompressing $\{I_{ij}^n\}$ by some coder. Then

$$PSNR_{nf} = 10\log_{10}(255^2 / MSE_{nf}) \qquad (1)$$

where $MSE_{nf} = \sum_{i=1}^{I}\sum_{j=1}^{J}(I_{ij}^d - I_{ij})^2 / IJ$ and

$$PSNR_{or} = 10\log_{10}(255^2 / MSE_{or}) \qquad (2)$$

where $MSE_{or} = \sum_{i=1}^{I}\sum_{j=1}^{J}(I_{ij}^d - I_{ij}^n)^2 / IJ$, I, J denote image size.

Now let us consider as an example [10] the dependences of $PSNR_{nf}$ and $PSNR_{or}$ on bpp for the test gray-scale image Lena in conventional 8-bit representation for σ^2=200 (see Fig. 1).

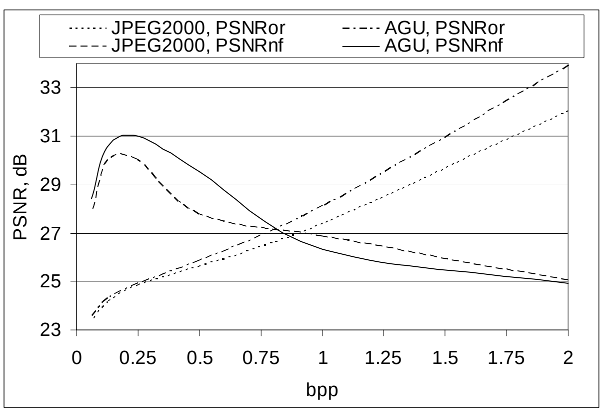

Figure 1 - Dependences of $PSNR_{nf}$ and $PSNR_{or}$ on bpp

One can see that $PSNR_{or}$ decreases with a reduction of bpp (i.e., with an increase of CR) for both JPEG2000 [12] and AGU [11] coders. At the same time, both curves of $PSNR_{nf}$ versus bpp have maxima for bpp≈0.24 that can be considered as OOP. In the neighborhood of OOP the coder AGU (available from http://www.cs.tut.fi/~karen/agucoder.htm) outperforms JPEG2000. Recall that AGU is based on DCT in 32x32 pixel blocks, the use of sophisticated probability models for coding of quantized DCT coefficients and on applying of decompressed image post-filtering for de-blocking [11]. We further concentrate on considering automatic procedure of accessing OOP just for this coder. Note, that the proposed approach is applicable also to other transform based coders.

In [10], by the joint analysis of the plots $PSNR_{nf}$(bpp) and $PSNR_{or}$(bpp) it has been established that the maximal $PSNR_{nf}$ was observed for such bpp when $PSNR_{or}$ became equal to T=10log$_{10}$(255^2/σ^2). In particular, for σ^2=200 (see plots in Fig. 1) one has T=25.12dB and for $PSNR_{or}$=T (when the curve $PSNR_{or}$(bpp) crosses the level T), OOP for the curves $PSNR_{nf}$(bpp) is observed (bpp≈0.24). Then, to calculate T one has to *a priori* know or to pre-estimate σ^2. The latter can be done with an appropriate accuracy in automatic mode at the first stage. In particular, the approaches proposed in our papers [13, 14] can be used. The second stage is to automatically determine bpp (CR) for OOP by analysing the curve $PSNR_{or}$(bpp). For this purpose, in [10] it was proposed to obtain several values for this curve and then, by using linear interpolation, to determine OOP when $PSNR_{or}$(bpp) crosses the level T. Obviously, for this purpose one needs to compress and decompress an image several times. Commonly, from 3 to 6 iterations are enough and this requires some time. To get around this shortcoming, in the next Section we propose a new approach for transform based coders to perform compression with accessing OOP at once (without any iterations and without decompression at all).

3. PROPOSED APPROACH TO AUTOMATIC ACCESSING OOP FOR AGU CODER

Note that for the most of transform base coders, in particular, AGU coder, CR (and, respectively, bpp) is controlled (varied) by changing a quantization step QS. In fact, for this coder the curve $PSNR_{or}$(bpp) in automatic determination of OOP [10] is replaced by the curve $PSNR_{or}$(QS) and for OOP the corresponding QS_{OOP} is obtained by interpolation of this curve.

Let us demonstrate that accessing OOP for AGU coder can be performed simpler. Suppose that one has σ^2 or its appropriately accurate estimate. Consider the plots of MSE_{nf} vs. QS_n where QS=σQS_n. Such plots are presented in Figures 2…6 for the 512x512 grey scale test images Baboon, Barbara, Goldhill, Lena, Peppers. The plots have been obtained for three values of σ^2, namely, 50, 100, and 400. The corresponding MSE_{nf} are denoted as MSE50, MSE100, MSE400.

Note that minimal values of MSE_{nf} for the curves MSE_{nf}(QS_n) correspond to OOPs. It is easy to see that such minimums are observed for almost all test images and for all considered values of σ^2. The only exception is the test image Baboon corrupted by noise with σ^2 equal to 50 and 100 (Fig. 2). Moreover, for all curves having minimums, these minimums take place for QS_n≈4.5. This phenomenon allows to propose the following automatic procedure for accessing OOP for AGU coder: estimate σ^2 by the method [13] or [14] → calculate QS_{OOP}=4.5σ → apply compression with QS_{OOP}.

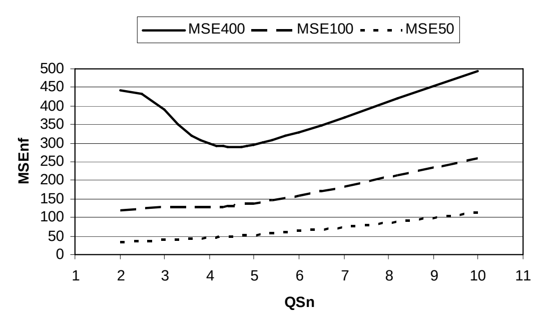

Figure 2 - Dependences MSE_{nf}(QS_n) for the test image Baboon

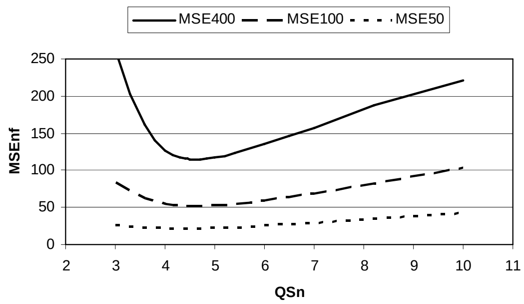

Figure 3 - Dependences $MSE_{nf}(QS_n)$ for the test image Barbara

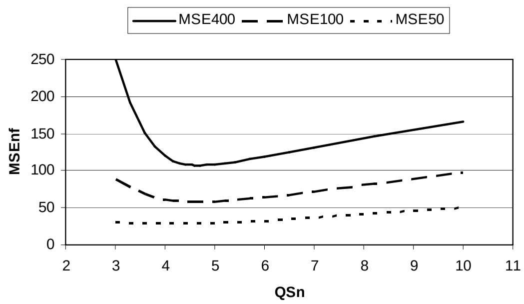

Figure 4 - Dependences $MSE_{nf}(QS_n)$ for the test image Goldhill

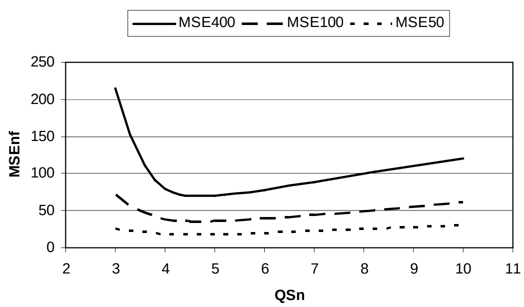

Figure 5 - Dependences $MSE_{nf}(QS_n)$ for the test image Lena

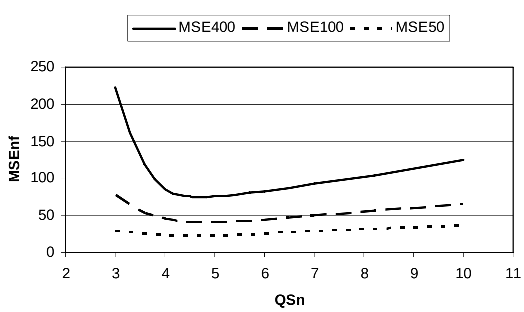

Figure 6 - Dependences $MSE_{nf}(QS_n)$ for the test image Peppers

The fact that QS_{OOP}=4.5σ has its intuitive explanation. Recall that compression of noisy images performs similarly to image hard threshold denoising [9,10] in the sense that zero values are assigned to spectral coefficients that have small absolute values (and basically correspond to noise) after quantization. Commonly it is considered that the optimal hard threshold is at about 2.7σ and then QS should be at about 5.4σ. But larger QS introduce larger distortions to spectral coefficients with relatively large absolute values due to increase of quantizations errors. Thus, a compromise between improving of noise reduction and increasing of distortions introduced with increasing of QS should exist. Luckily, it is observed for practically the same $QS_n\approx$4.5 irrespectively to an image to be compressed and noise variance.

Consider a particular example of the test image Barbara corrupted by an additive Gaussian noise with σ^2=100 (this image is presented in Fig. 7). The compressed image with QS_{OOP}=45 is shown in Fig. 8. As seen, despite the image has been compressed by more than 16 times, $PSNR_{nf}$ has increased by 2.8dB. This is due to noise suppression provided by compression and this effect is well seen from visual comparison of images in Figures 7 and 8. Note that efficient denoising for the considered test image and noise variance produces $PSNR_{nf}\approx$ 33.5 dB [15]. The difference in $PSNR_{nf}$ for compressed and denoised images is explained by quantization errors (distortions) introduced by compression.

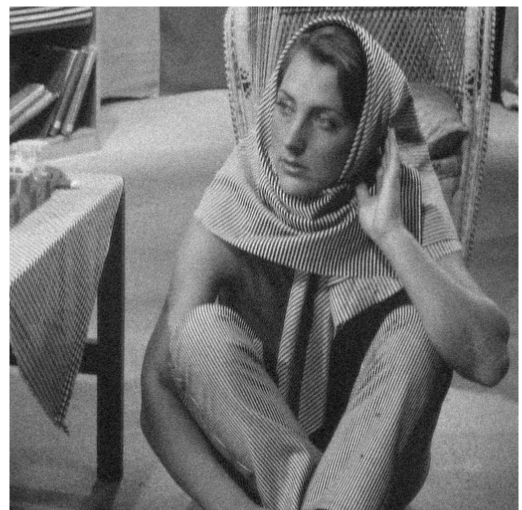

Figure 7 - Noisy image Barbara, σ^2=100, $PSNR_{nf}$ =28.13 dB

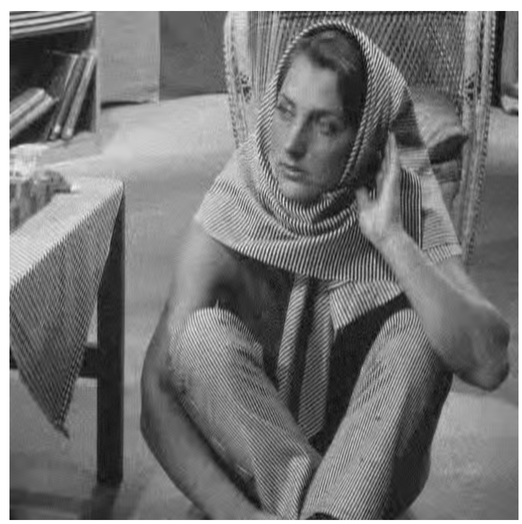

Figure 8 - Compressed image Barbara with QS_{OOP}=45, the obtained bpp=0.48, $PSNR_{nf}$ =30.95 dB

4. NOISE-FREE IMAGE COMPRESSION

Consider a practical situation when one does not know a priori is an image (to be compressed) corrupted by a noise or it is noise-free. Then, applying an automatic procedure of noise variance evaluation (e.g.,[13] or [14]), one anyway gets some estimate of noise variance which commonly differs from zero even if an image under interest is noise-free. In other words, the techniques [13], [14] produce slightly biased estimations of variance although they are more accurate than many other existing methods.

To analyze what happens in this case with a performance of the procedure of automatic selection of QS_{OOP} and compression of images, we have carried out the following study. For the considered test images, the values of estimates of σ^2 obtained in [13], [14] were taken for determination of QS_{OOP} and the corresponding compression was done. After this, we determined $PSNR_{nf}$ and bpp for the compressed images (note that in this case $PSNR_{nf}=PSNR_{or}$). The values of $PSNR_{nf}$ and bpp are presented in Table 1. Moreover, for the obtained bpp values, compression of noise-free images by JPEG2000 [12] was performed and the corresponding values of $PSNR_{nf}$ were calculated. They are also presented in Table 1.

Table 1. Performance analysis for noise-free image compression by AGU and JPEG2000.

Image	Estimate of σ^2	bpp for QS_{OOP}	AGU, $PSNR_{nf}$, dB	JPEG2000, $PSNR_{nf}$, dB
Baboon	14.16	1.92	35.12	34.23
Barbara	2.87	1.57	42.69	41.72
Goldhill	2.75	1.91	42.13	41.35
Lena	5.50	0.95	40.28	40.03
Peppers	5.31	1.33	39.97	39.64

As seen, the largest estimate of σ^2 is obtained for the test image Baboon that is the most textural. A bpp value for it is the largest. The provided $PSNR_{nf}$ values are different for all images. For AGU coder they are always better than for JPEG2000. The most important thing is that the provided values of $PSNR_{nf}$ are within such a range (they are larger than 35 dB for AGU and 34 dB for JPEG2000) that distortions introduced by compression are practically not observed visually in decompressed images. Thus, we can state that the proposed automatic procedure originally designed for lossy compression of noisy images performs appropriately well for compressing noise-free images.

5. CONCLUSIONS

An effective automatic procedure for lossy image compression accessing OOP based on automatic evaluation of noise variance and determination of the quantization step for transform based coders is designed. It is demonstrated that this procedure provides a good compromise between compressed image quality and compression ratio. Moreover, it is also applicable if original images are noise-free.

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