Scan-based Quality Control for JPEG2000 using R-D Models

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ABSTRACT

JPEG 2000 compression of very large images (e.g. medical imaging, microscopy, satellite images, photography) requires tiling processing. Tiling processing results in border artifacts. Scan-based wavelet transform avoids these artifacts. However scan-based methods using rate control result in poor local quality control. Most of applications require quality control image coding without any real time rate constraint (e.g. off-line compression for storage or for broadcasting over IP, ADSL ...). Therefore, we propose a new scan-based wavelet transform compression algorithm based on quality control for JPEG 2000-like codecs. The method proposed in this paper ensures accurate local quality control and can provide a global rate-distortion improvement up to 1.7 dB in PSNR comparatively to a rate control procedure.

1 Introduction

JPEG 2000 is now considered as a top-level codec for still image coding. However very large images (e.g. medical imaging, microscopy, satellite images, high definition photography) cannot be globally compressed on forthcoming industrial chips since they are generally limited in memory to a given input image size (e.g. 128x128 pixels for the CS6510 JPEG 2000 Encoder chip [1]). In order to overcome this problem, JPEG 2000 standard includes a tiling processing option. It is well known that tiling processing results in border artifacts. Scan-based wavelet transform [2, 3] is an efficient method to overcome this drawback. However scan-based wavelet transforms were historically associated with rate control [4]. Rate control produces undesirable variations (oscillations) of the local image quality. Moreover, most applications require quality image control adapted to the end-user application and do not require any real time rate constraint (e.g. off-line compression for storage or for broadcasting over IP or ADSL, real time compression with possible buffering...).

In this paper, conversely to rate control scan-based methods, we propose a new scan-based wavelet transform compression algorithm based on quality control. Let the quality measure be the mean squared error (MSE) or PSNR. Our algorithm ensures a local quality control of the final image avoiding both tiling artifacts and local image quality variations.

In section 2, we present the global scan-based compression scheme. Section 3 is devoted to the MSE allocation and quality control procedures and section 4 shows some experimental results.

2 Compression scheme

Fig. 1 shows the flow chart of our quality controled compression scheme. The first step of the method is the scan-based or tiling computation of the image wavelet decomposition. In this paper we use scan-based DWT but the method can be straightforward adapted to tiling for JPEG 2000 [5]. Then, we use statistical information of the wavelet coefficients to compute an optimized model-based MSE allocation. In the third step, we apply scalar quantizers with optimized deadzone size in each subband [6]. Finally, the quantized wavelet coefficients are lossless entropy encoded using JPEG 2000's bit plane context-based arithmetic coder [5]. We also use a classical quality control loop to match the exact quality constraint. An important aspect of our approach is that once the MSE allocation has been computed, the quantization and encoding of subbands is done separately and can be performed concurrently for each subband.

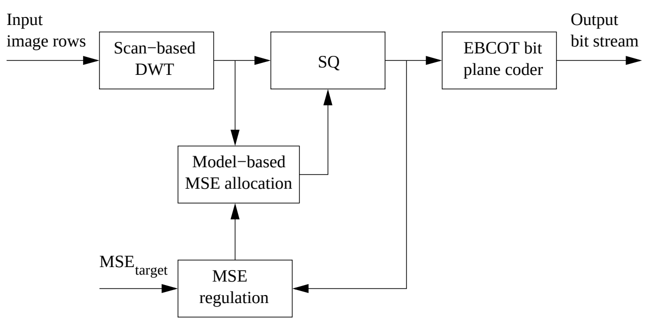

Figure 1: Flow chart of the compression scheme

We have selected the 9-7 biorthogonal wavelet transform [7], which is known to be almost orthogonal and gives the best results for dyadic sampled images [8]. We use a three level decomposition DWT and compute it on-the-fly to avoid blocking artifacts introduced by spatial tiling. The sets of coefficients processed together are made up of all the coefficients which have been obtained by a filter (or convolution of filters) centered on one of the rows of a given spatial region [9]. For example, we will perform the compression of wavelet coefficients for each block of eight image rows. The corresponding wavelet coefficients are sets of four rows of coefficients in the high frequency subbands, two rows of coefficients in the middle frequency subbands and one row of coefficients in the remaining subbands. Further information on scan-based wavelet transform computation are available in [9, 2, 10, 3].

3 MSE allocation and regulation

3.1 General purpose

The purpose of the MSE allocation procedure is to determine the quantizers in each subband which minimize the total bitrate for a target MSE. The subband quantizers are scalar quantizers with optimized deadzone size. They are defined by the size of their zero quantization bin z and the size of all other quantization bins q. Therefore, the solution of the MSE allocation problem is obtained by the minimization of the following criterion using Lagrange operators:

$$J = \sum_{i=1}^{\#SB} a_i R_i(z_i, q_i) + \lambda \left(\sum_{i=1}^{\#SB} \pi_i \sigma_{Q_i}^2(z_i, q_i) - D_T \right) \quad (1)$$

where $R_i(z_i, q_i)$ and $\sigma_{Q_i}^2(z_i, q_i)$ are respectively the bitrate and the MSE produced in the i^{th} subband; a_i denotes the weight of subband i in the total bitrate and $\{\pi_i\}$ are weights used to take account of the non-orthogonality of the filter bank. $\#SB$ denotes the number of subbands while D_T is the target MSE.

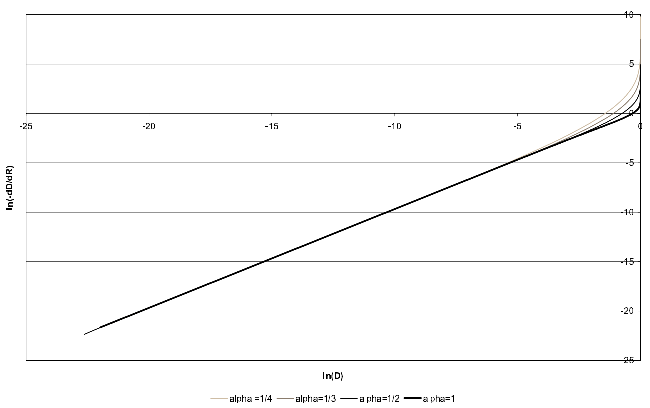

Figure 2: $ln(-h)$ versus $ln\,(D)$

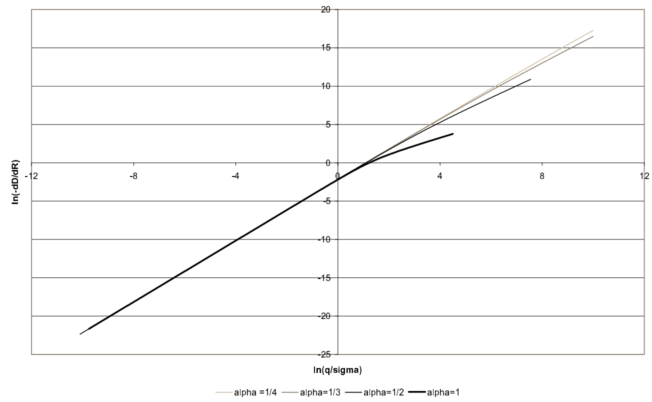

Figure 3: $ln(-h)$ versus $ln\left(\frac{q}{\sigma}\right)$

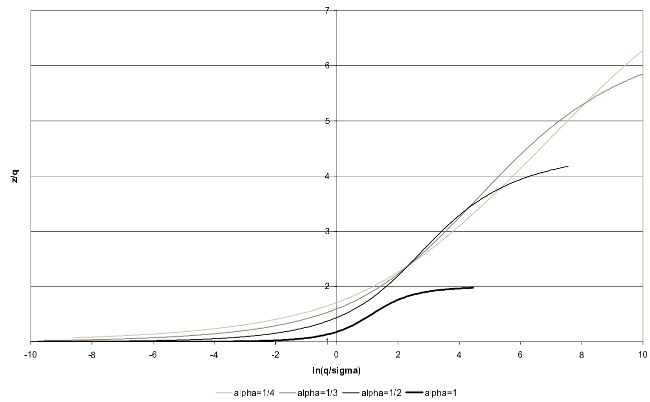

Figure 4: Optimal $\frac{z}{q}$ ratio versus $ln\left(\frac{q}{\sigma}\right)$

3.2 Rate and distortion models

The only way to compute an efficient MSE allocation without pre-quantizing subbands is to accurately model the distribution $p(x)$ of the wavelet coefficients and use theoretical models for both distortion and bitrate. This distribution can be approximated with generalized gaussians [7]. We have

$$p(x) = ae^{-|bx|^{\alpha}}$$

with $b = \frac{1}{\sigma}\sqrt{\frac{\Gamma(3/\alpha)}{\Gamma(1/\alpha)}}$ and $a = \frac{b\alpha}{2\Gamma(1/\alpha)}$. To compute the bitrate produced by the deadzone scalar quantizer $\{z, q\}$, we use the probability of the quantization level m. We have $\Pr(m) = \Pr(-m) = \int_{\frac{z}{2}+(|m|-1)q}^{\frac{z}{2}+|m|q} p(x)\,dx$ for $m \neq 0$ and $\Pr(0) = \int_{-\frac{z}{2}}^{+\frac{z}{2}} p(x)\,dx$.

Then, the bitrate is approximated by the entropy of the output quantization levels:

$$R = -\sum_{m=-\infty}^{+\infty} \Pr(m) \log_2 \Pr(m)$$

According to [11], the best decoding value for the quantization level m is the centroid of its quantization bin $\widehat{x_m} = \frac{\int_{\frac{z}{2}+(|m|-1)q}^{\frac{z}{2}+|m|q} xp(x)dx}{\Pr(m)}$ for $m \neq 0$ and $\widehat{x_0} = 0$. Then, the mean squared error is

$$\begin{aligned}\sigma_Q^2 &= \int_{-\frac{z}{2}}^{+\frac{z}{2}} x^2 p(x)\,dx \\ &+2\sum_{m=1}^{+\infty} \int_{\frac{z}{2}+(|m|-1)q}^{\frac{z}{2}+|m|q} (x-\widehat{x_m})^2\, p(x)\,dx\end{aligned}$$

3.3 Solution

For generalized gaussian distributions, (1) can be written as

$$J = \sum_{i=1}^{\#SB} a_i R_i(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}) + \lambda \left(\sum_{i=1}^{\#SB} \pi_i \sigma_i^2 D_i(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}) - D_T \right) \quad (2)$$

where R_i and D_i depend only on α and the ratios $\frac{z}{\sigma}$ and $\frac{q}{\sigma}$ (see [6] for more details).

Let f be any function and x_k its k^{th} variable and define $\frac{\partial f}{\partial x_k}$ as the derivative of f with respect to its k^{th} variable. Differentiating (2) with respect to z_i, q_i and λ provides the following system:

$$\frac{\frac{\partial D_i}{\partial x_1}\left(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}\right)}{\frac{\partial R_i}{\partial x_1}\left(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}\right)} = \frac{\frac{\partial D_i}{\partial x_2}\left(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}\right)}{\frac{\partial R_i}{\partial x_2}\left(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}\right)} \quad (3)$$

$$\frac{\frac{\partial D_i}{\partial x_2}\left(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}\right)}{\frac{\partial R_i}{\partial x_2}\left(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}\right)} = -\frac{a_i}{\lambda \pi_i \sigma_i^2} \quad (4)$$

$$\sum_{i=1}^{\#SB} \pi_i \sigma_i^2 D_i \left(\frac{z_i}{\sigma_i}, \frac{q_i}{\sigma_i}\right) - D_T = 0 \quad (5)$$

The solution of Eq. (3) provides the optimal relationship between z and q for a given shape parameter α. We get $\frac{z_i}{\sigma_i} = g_i\left(\frac{q_i}{\sigma_i}\right)$ with g_i the function that provides the solution of (3). Inserting this in Eq. (4) and (5) gives

$$h_i\left(\frac{q_i}{\sigma_i}\right) = \frac{\frac{\partial D_i}{\partial x_2}\left(g_i\left(\frac{q_i}{\sigma_i}\right), \frac{q_i}{\sigma_i}\right)}{\frac{\partial R_i}{\partial x_2}\left(g_i\left(\frac{q_i}{\sigma_i}\right), \frac{q_i}{\sigma_i}\right)} = -\frac{a_i}{\lambda \pi_i \sigma_i^2} \quad (6)$$

$$\sum_{i=1}^{\#SB} \pi_i \sigma_i^2 D_i \left(g_i\left(\frac{q_i}{\sigma_i}\right), \frac{q_i}{\sigma_i}\right) - D_T = 0 \quad (7)$$

where h_i is defined in Eq. (6) to simplify the notations.

The bit allocation process is the following:

1. Lambda is given. For each subband i, compute $\ln\left(\frac{a_i}{\lambda \pi_i \sigma_i^2}\right) = \ln(-h)$ and read the corresponding normalized mean squared error D_i from the curves shown in Fig. 2.

2. Compute $\left|\sum_{i=1}^{\#SB} \pi_i \sigma_i^2 D_i - D_T\right|$. If it is lower than a given threshold, the constraint (7) is verified. Else, compute a new λ and go back to step 1.

3. For each subband i, read $\frac{q_i}{\sigma_i}$ from the curves shown in Fig. 3. q_i is the optimal quantization step for subband i.

4. Then, for each subband i, read z_i from the curves shown in Fig. 4.

3.4 Regulation

The wavelet coefficients encoding is performed for each group of eight image rows. The output MSE is estimated from the measured mean squared quantization errors of each subband with $MSE_{output} = \sum_{i=1}^{\#SB} \pi_i MSE_i$. Finally, MSE variations are controled with a Proportional Integral MSE control unit.

4 Experimental results

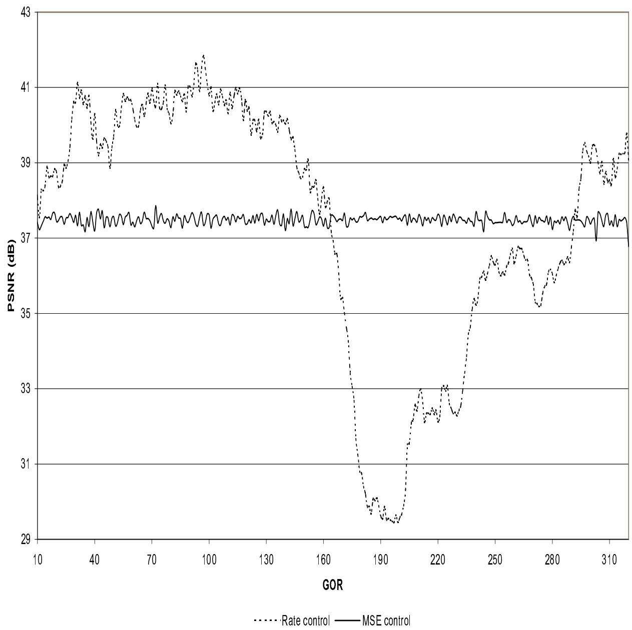

Figure 5: PSNR of each Group Of Rows (GOR) for Woman. GOR of 8 image rows. Global bitrate: 1 bpp.

We compare the proposed compression scheme with a similar compression scheme based on rate regulation. Both coders use optimized deadzone quantizers and JPEG 2000's bit plane context-based arithmetic coder. We apply both coders on *Woman* from the JPEG 2000 database base (see Fig. 7). From Fig. 5, we notice that for the same global bitrate, the rate regulation provides local PSNR variations up to 12 dB. On the contrary, the proposed method allows an accurate local PSNR control with variations lower than 1 dB. Furthermore, Fig. 6 shows a global rate-distortion improvement of 1 dB to 1.7 dB with our method. Therefore, the proposed method provides both local PSNR control and possible global PSNR improvement.

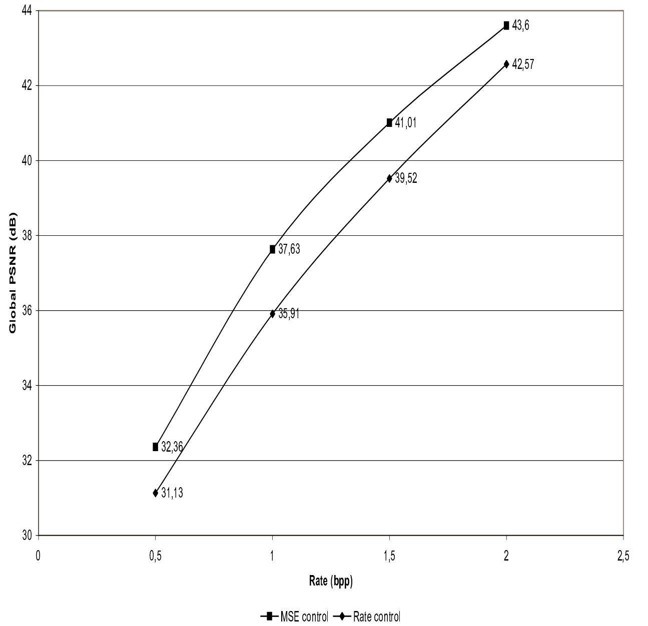

Figure 6: Global PSNR versus global bitrate for compression schemes with MSE regulation and rate regulation. Image Woman processed with Group of Rows of 8 image rows.

5 Conclusion

The method proposed in this paper provides high efficiency local quality control. Furthermore, our simulations show a possible global rate-distortion improvement up to 1.7 dB. Therefore, our method is a good candidate for compression applications which require controled local quality (e.g. medical imaging, high resolution photography, microscopy, satellite images).

Figure 7: *Woman* (grayscale, 2048x2560, 8 bpp)

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