OPTIMAL COLOR IMAGE COMPRESSION USING LOCALIZED COLOR COMPONENTS TRANSFORMS

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ABSTRACT

Most compression techniques for color images are based on de-correlating the color primaries. Recently, however, a new approach to color image compression, based on exploiting the correlations between the color components, has been presented, outperforming the common de-correlation approach. In this work we introduce an optimized method that generalizes both approaches of correlation and de-correlation and derive its Rate-Distortion (R-D) model. The optimization is based on the selection of localized Color Components Transforms for the compression process. The new method provides results significantly superior to JPEG2000 with respect to all distortion measures and visual quality, while keeping the complexity comparable with JPEG2000.

1. INTRODUCTION

The common approach to color image coding is the de-correlation method. It consists of applying a Color Components Transform (CCT) to the RGB color components to reduce their high inter-color correlations [1], [2], [3] and then coding each color component separately. JPEG [4] and JPEG2000 [5], [6] are examples of algorithms employing this approach. This approach has also been presented in [7] in a general framework that allows the optimization of the CCT and quantization stages based on a Rate-Distortion theory for subband transform coders. Another approach, based on exploiting the color correlation, was presented in a general optimization framework in [8] and found superior to the de-correlation method [9]. This approach utilizes the inter-color correlation of the color components to encode two of them as a polynomial approximation of the third in each frequency band of the subband transform used. Earlier versions of this approach can be found in [10] and [11].
In this work we present a new method for color image compression that generalizes both approaches. We derive and optimize its R-D behavior. This optimization provides new insight into the locally optimal choice of the CCT in each subband. It is also the basis for a new compression algorithm using this choice of the CCT.

2. THE DE-CORRELATION AND THE CORRELATION BASED METHODS

2.1 The De-correlation Based Approach

The de-correlation method considers a general color subband transform coder consisting of the following stages.

1. Pre-processing: a CCT is applied to the RGB color components. If we denote the RGB components in vector form as $\mathbf{x} = [R\ G\ B]^T$ and the new color components as $\widetilde{\mathbf{x}} = [C_1\ C_2\ C_3]^T$, then $\widetilde{\mathbf{x}} = \mathbf{M}\mathbf{x}$, where $\mathbf{M}$ denotes the CCT matrix.
2. Subband transforming and quantizing: a subband transform is applied to each color component. Then the transform coefficients are quantized using a uniform scalar quantizer for each subband.
3. Post-processing: the quantized coefficients are losslessly coded using techniques such as run-length coding, zero trees, delta modulation and entropy coding.

The Rate-Distortion model of this algorithm is [7]:

$$d\left(\{R_{bi}\},\mathbf{M}\right) = \frac{1}{3}\sum_{i=1}^{3}\sum_{b=0}^{B-1}\eta_b G_b \widetilde{\sigma}_{bi}^2 \varepsilon_i^2 e^{-aR_{bi}}\left((\mathbf{M}\mathbf{M}^T)^{-1}\right)_{ii}, \tag{1}$$

where d is the average MSE (Mean Square Error) distortion of the image in RGB domain, $\widetilde{\sigma}_{bi}^2$ is the variance of subband b ($b \in 0,1,\ldots,B-1$) of color component C_i, G_b is its energy gain, η_b is its sample rate [12] and R_{bi} is the rate allocated to it. Also ε_i^2 is a constant dependent upon the distribution of color component i and a is a constant equal to $2ln2$.
Optimal rates allocation for the subbands can be found by minimizing the expression of (1) under a rate constraint [7].

2.2 The Correlation Based Approach

In the correlation-based method a general subband transform is considered as well. A description of the algorithm stages follows.

- In the pre-processing stage a CCT is applied to the color primaries with the goal of raising the inter-color correlations without greatly increasing the condition number of the CCT [8]. Mathematically, this stage is the same as for the de-correlation method.
- In the coding stage one of the new color components (C_1, C_2 or C_3) is chosen to be the base color and the other two (the dependent colors) are approximated as a first order polynomial function of the base. Prior to the approximation, a subband transform is applied to each of the colors and the approximation is performed in each subband separately. Denoting the subband b coefficients of C_i as $y_b^{C_i}$, the approximation in each subband is according to:

$$\begin{aligned}\hat{y}_b^{C_2} &= \tau_{b1}\cdot y_b^{C_1} + \tau_{b0}\\ \hat{y}_b^{C_3} &= \beta_{b1}\cdot y_b^{C_1} + \beta_{b0}.\end{aligned} \tag{2}$$

Here C1 is assumed to be the base and C2 and C3 are the dependent colors. $\hat{y}_b^{C_2}$ and $\hat{y}_b^{C_3}$ denote the approximated coefficients of subband b of C2 and C3, respectively. The expansion coefficients τ_{b1}, τ_{b0} for C2 and β_{b1}, β_{b0} for C3 are calculated according to the least squares (LS) method [8]. In this work we consider a correlation-based scheme in which only the following first order coefficients τ_{b1} and β_{b1} are sent:

$$\tau_{b1} = \frac{cov\left(y_b^{C_1}, y_b^{C_2}\right)}{var(y_b^{C_1})} \qquad \beta_{b1} = \frac{cov\left(y_b^{C_1}, y_b^{C_3}\right)}{var(y_b^{C_1})}. \tag{3}$$

After calculating the expansion coefficients (quantized and reconstructed) the approximation errors are calculated and coded. The errors in subband b are given by:

$$e_b^{C_2} = y_b^{C_2} - \widetilde{\tau}_{b1} \cdot y_b^{C_1}, \qquad e_b^{C_3} = y_b^{C_3} - \widetilde{\beta}_{b1} \cdot y_b^{C_1} \tag{4}$$

for C_2 and C_3 respectively. Note that $\widetilde{\tau}_{b1}$, $\widetilde{\beta}_{b1}$ denote the reconstructed expansion coefficients.
Optimal rates are determined for the three color components and are used to derive the optimal quantization steps, passed to the quantizers. An independent uniform quantizer is employed in each subband.

- The post-processing stage employs lossless techniques to reduce the required bit budget as in the de-correlation based approach.

3. A GENERALIZED APPROACH - CORRELATION/DE-CORRELATION

The idea of the new approach is that instead of using a global CCT (the same for all the subbands as in the previous approaches) we first apply a subband transform (SBT) to each of the RGB color components and then use local CCTs to de-correlate the SBT coefficients of each subband separately. Further coding can be done by quantization and post-processing stages. We denote the local CCT of subband b by $\mathbf{M_b}$. First we would like to develop the MSE expression of this new compression scheme. Then we would like to consider the optimal choice of the local CCTs.
Note that the new scheme generalizes the de-correlation approach in the special case of $\mathbf{M_b} = \mathbf{M}$ in each subband. Moreover, with a simple extension it is also a generalization of the correlation-based approach. In the following discussion we use the notations of $\mathbf{Y_b} = [y_b^R \; y_b^G \; y_b^B]^T$ and $\widetilde{\mathbf{Y}}_\mathbf{b} = [y_b^{C_1} \; y_b^{C_2} \; y_b^{C_3}]^T$ for the vectors of the SBT coefficients (of the three color components) at some index in subband b in the RGB and in the C1C2C3 color spaces, respectively. Here y_b^R, for example, denotes the SBT coefficient at some index in subband b of the Red component. The operation of the local CCT in subband b is

$$\widetilde{\mathbf{Y}}_\mathbf{b} = \mathbf{M_b}\mathbf{Y_b}. \tag{5}$$

Now, we would like to consider the following generalization:

$$\widetilde{\mathbf{Y}}_\mathbf{b} = \mathbf{M_b}\mathbf{Y_b} + \begin{bmatrix} g1 \\ g2 \\ g3 \end{bmatrix} \tag{6}$$

for some constants g_1, g_2, g_3. The coefficients can be chosen as $g_i = 0, \; i \in \{1,2,3\}$ for the de-correlation approach. The correlation-based method, on the other hand, applies a global CCT $\mathbf{M}$ first and then does LS approximation of the new C2 and C3 color components relative to C1. This can be described mathematically as:

$$\widetilde{\mathbf{Y}}_\mathbf{b} = \begin{pmatrix} 1 & 0 & 0 \\ -\tau_{b1} & 1 & 0 \\ -\beta_{b1} & 0 & 1 \end{pmatrix} \mathbf{M}\mathbf{Y_b} + \begin{bmatrix} 0 \\ \tau_{b0} \\ \beta_{b0} \end{bmatrix}, \tag{7}$$

where τ_{b0}, τ_{b1} and β_{b0}, β_{b1} are those introduced in (2). Clearly, (7) is a private case of (6). Thus the new scheme described by (6) generalizes both the de-correlation and the correlation-based approaches and hence it will be referred to as the Correlation De-correlation Based Approach (CDBA).

3.1 MSE expression for the CDBA scheme

When considering the simple CDBA scheme of (5), we would like to find the expression for the MSE of the subbands in the RGB domain. The error covariance matrices for the subband b in the RGB and C1C2C3 domains are

$$\begin{aligned} \mathbf{Er_b} &= E\left[(\mathbf{Y_b} - \mathbf{Y_b^{rec}})(\mathbf{Y_b} - \mathbf{Y_b^{rec}})^T\right] \quad \text{and} \\ \widetilde{\mathbf{Er}}_\mathbf{b} &= E\left[(\widetilde{\mathbf{Y}}_\mathbf{b} - \widetilde{\mathbf{Y}}_\mathbf{b}^{\mathbf{rec}})(\widetilde{\mathbf{Y}}_\mathbf{b} - \widetilde{\mathbf{Y}}_\mathbf{b}^{\mathbf{rec}})^T\right] \end{aligned} \tag{8}$$

respectively, where $\mathbf{Y_b^{rec}}$ denotes $\mathbf{Y_b}$ coded and reconstructed and $E()$ stands for statistic mean. According to (5) $\mathbf{Y_b} = \mathbf{M_b^{-1}}\widetilde{\mathbf{Y}}_\mathbf{b}$, so we can write $\mathbf{Er_b} = \mathbf{M}^{-1}\widetilde{\mathbf{Er}}_\mathbf{b}\mathbf{M}^{-T}$. The MSE distortions d_{bi} of the RGB color components in subband b are the diagonal elements of $\mathbf{Er_b}$ and thus:

$$d_{bi} = \mathbf{n_{bi}}^T \widetilde{\mathbf{Er}}_\mathbf{b} \mathbf{n_{bi}}, \tag{9}$$

where $\mathbf{n_{bi}}$ is the i^{th} row of $\mathbf{M_b}^{-1}$ in column form. In a similar fashion, the diagonal elements of $\widetilde{\mathbf{Er}}_\mathbf{b}$ are the MSE distortions $\widetilde{d}_{bi}$ of the C_1, C_2, C_3 color components, given by [7]:

$$\widetilde{d}_{bi} = \varepsilon_i^2 \widetilde{\sigma}_{bi}^2 e^{-aR_{bi}}. \tag{10}$$

Assuming that the quantization errors in each subband in the C1C2C3 domain are uncorrelated, $\widetilde{\mathbf{Er}}_\mathbf{b}$ becomes diagonal. Then after substitution of (10) for $\widetilde{d}_{bk}$, (9) becomes

$$d_{bi} = \sum_{k=1}^{3} (\mathbf{n_{bi}})_k^2 \widetilde{d}_{bk} = \sum_{k=1}^{3} \left(\mathbf{M_b}^{-1}\right)_{ik}^2 \varepsilon_k^2 \widetilde{\sigma}_{bk}^2 e^{-aR_{bk}} \tag{11}$$

Now using the notation $\mathbf{x} = [R \; G \; B]^T$ we can write for the MSE of the color component i in the image domain [12]:

$$MSE\left(\mathbf{x}_i\right) = \sum_{b=0}^{B-1} \eta_b G_b d_{bi}. \tag{12}$$

where η_b and G_b are defined following Equation (1). Also the average MSE in RGB domain is simply:

$$MSE = \frac{1}{3}\sum_{i=1}^{3} MSE\left(\mathbf{x}_i\right) = \frac{1}{3}\sum_{i=1}^{3}\sum_{b=0}^{B-1} \eta_b G_b d_{bi}. \tag{13}$$

Substituting (11) in (13) and rearranging the terms we get:

$$MSE = \frac{1}{3}\sum_{k=1}^{3}\sum_{b=0}^{B-1} \eta_b G_b \varepsilon_k^2 \widetilde{\sigma}_{bk}^2 e^{-aR_{bk}} \sum_{i=1}^{3} \left(\mathbf{M_b}^{-1}\right)_{ik}^2. \tag{14}$$

It can be shown that $\sum_{i=1}^{3}\left(\mathbf{M_b}^{-1}\right)_{ik}^{2}=\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}$ and thus we can write (14) as

$$MSE = \frac{1}{3}\sum_{k=1}^{3}\sum_{b=0}^{B-1}\eta_b G_b \varepsilon_k^2 \widetilde{\sigma}_{bk}^2 e^{-aR_{bk}}\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}. \tag{15}$$

3.2 Optimization of the CDBA scheme

3.2.1 The optimal rates

Assuming a total image rate R and minimizing the MSE expression of (15) under the rate constraint $\sum_{i=1}^{3}\alpha_i\sum_{b=0}^{B-1}\eta_b R_{bi} = R$ and non-negativity constraints results in the following solution for the optimal rates:

$$R_{bi} = \frac{R}{\sum\limits_{j=1}^{3}\alpha_j\xi_j} + \frac{1}{a}ln\left(\frac{\frac{\varepsilon_i^2 G_b\widetilde{\sigma}_{bi}^2\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}}{\alpha_i}}{\prod_{k=1}^{3}\left(\frac{GM_k^{Act}\varepsilon_k^2\Phi_k^{Act}}{\alpha_k}\right)^{\frac{\alpha_k\xi_k}{\sum_{j=1}^{3}\alpha_j\xi_j}}}\right). \tag{16}$$

α_i above are down-sampling factors [7] and GM_k^{Act} and ξ_k are given by

$$\xi_i \triangleq \sum_{b\in Act_i}\eta_b,\quad GM_i^{Act} \triangleq \prod_{b\in Act_i}\left(G_b\widetilde{\sigma}_{bi}^2\right)^{\frac{\eta_b}{\xi_i}} \tag{17}$$

using the definition of Act_i (the set of the active subbands or the subbands with non-zero rates in color component i) given by $Act_i \triangleq \{b\in[0,B-1]\,|\,R_{bi}>0\}$. Also Φ_k^{Act} is

$$\Phi_k^{Act} \triangleq \prod_{b\in Act_k}\left[\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}\right]^{\frac{\eta_b}{\xi_k}}. \tag{18}$$

3.2.2 The optimal choice for local CCT

Substituting (16) in (15) we can easily derive that

$$MSE = \frac{1}{3}e^{\left(\frac{-aR}{\sum_{j=1}^{3}\alpha_j\xi_j}\right)}\left(\sum_{i=1}^{3}\alpha_i\xi_i\right)\prod_{k=1}^{3}\left(\frac{GM_k^{Act}\varepsilon_k^2\Phi_k^{Act}}{\alpha_k}\right)^{\frac{\alpha_k\xi_k}{\sum_{j=1}^{3}\alpha_j\xi_j}} + \sum_{k=1}^{3}\sum_{b\notin Act_k}\eta_b G_b\varepsilon_k^2\widetilde{\sigma}_{bk}^2\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}. \tag{19}$$

Here the first term is the contribution of the active subbands to the MSE and the second term of the non-active ones. We expect that the variances of the non-active subbands are small and thus neglect the second term. Also if we assume that ξ_j are approximately constant, then $\sum\limits_{j=1}^{3}\alpha_j\xi_j$ is constant and minimizing the MSE requires minimizing $\prod_{k=1}^{3}\left(\frac{GM_k^{Act}\Phi_k^{Act}}{\alpha_k}\right)^{\alpha_k\xi_k}$. Substituting (18) for Φ_k^{Act} and (17) for GM_k^{Act} and simplifying, we can write this expression as

$$f\left(\{\mathbf{M_b}\}\right) = \prod_{b\in Act_k}\left(\prod_{k=1}^{3}\left[\widetilde{\sigma}_{bk}^2\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}\right]^{\alpha_k}\right)^{\eta_b}. \tag{20}$$

Clearly, this function is a product of separate target functions for each subband and minimizing it is the same as minimizing $\prod_{k=1}^{3}\left[\widetilde{\sigma}_{bk}^2\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}\right]^{\alpha_k}$ for each subband. To express these separate functions by the image data only, we define the subband b covariance matrix $\mathbf{\Lambda_b}$ in the RGB domain:

$$\mathbf{\Lambda_b} \triangleq E\left[\left(\mathbf{Y_b}-\mu_{\mathbf{Y_b}}\right)\left(\mathbf{Y_b}-\mu_{\mathbf{Y_b}}\right)^T\right]\quad \mu_{\mathbf{Y_b}} \triangleq E\left[\mathbf{Y_b}\right], \tag{21}$$

so that we can write $\widetilde{\sigma}_{bi}^2 = \mathbf{m_{bi}}^T\mathbf{\Lambda_b}\mathbf{m_{bi}}$, where $\mathbf{m_{bi}}$ denotes row i of $\mathbf{M_b}$ in column vector form. For simplicity we assume no down-sampling is employed, thus the target function f_b to be minimized for subband b becomes

$$f_b\left(\mathbf{M_b}\right) = \prod_{k=1}^{3}\left(\mathbf{m_{bi}}\mathbf{\Lambda_b}\mathbf{m_{bi}}^T\right)\left((\mathbf{M_b}\mathbf{M_b}^T)^{-1}\right)_{kk}. \tag{22}$$

The minimization of this target function was discussed in [7] and it was derived that the KLT is the minimizer. Thus the optimal CCT at subband level in each active subband is the local KLT of this subband.

It can be shown that when down-sampling is used, the optimal choice for the CCT, i.e., the one minimizing the MSE of the reconstructed image, is still the local KLT in each subband [14].

4. THE CDBA COMPRESSION ALGORITHM

In this section we present a compression algorithm based on the CDBA scheme using the DWT (by the Daubechies 9/7 filter bank). The algorithm follows the next steps:

1. Calculate the DWT transform of each of the primary color components: Red, Green and Blue.
2. Calculate the KLT transform in each DWT subband.
3. Find the optimal rates using Equation (16).
4. Code the KLT matrices as described below and reconstruct them. The coding is for the active subbands only.
5. Apply the local CCT in each active subband. Place the transformed DWT coefficients with the most energy (variance) into C1 and the coefficients with the minimal energy into C3. The DWT coefficients of the non-active subbands are set to zero.
6. Quantize each of the C1, C2 and C3 color components using optimal quantization steps as in [7].
7. Apply the post-processing stage of the Embedded Zerotree Wavelet (EZW) algorithm [13] to further reduce the required bit budget.

Coding the local CCT matrices

The local CCT matrices have to be transmitted to the decoder. There are B matrices of size 3×3 for the whole image, however only the active subband matrices should be sent. Also not all the 9 elements of each CCT matrix have to be sent, but 4 are enough due to the following considerations:

1. The rows of each CCT matrix can be normalized, e.g., to L1 norm of 1, as done in this work. This normalization allows for reducing the number of matrix elements that need to be sent for each row to 2. Only the sign bit of the third coefficient is sent. Then the third coefficient of row i ($i\in\{1,2,3\}$) in subband b, denoted m_{i3}^b, can be reconstructed using the first two coefficients m_{i1}^b and m_{i2}^b

and the sign bit s^b_{i3} according to

$$m^b_{i3} = \left(1 - \left|m^b_{i1}\right| - \left|m^b_{i2}\right|\right) s^b_{i3}. \quad (23)$$

2. The rows of each KLT matrix are orthogonal. Thus only two rows can be sent and used to derive the third one using the orthogonality constraints.

The coding technique used for the CCT matrices is separate quantizing and coding of each CCT element for all the subbands. We scan the subbands in the order proposed in [13] from the coarsest resolution level to the finest and use delta modulation to exploit the correlations between the subbands. Then size/value representation is used with Huffman coding of the sizes and variable length integer codes for the values (similar to JPEG [4]).

5. COMPARISON OF THE CDBA SCHEME TO OTHER METHODS

The main comparison of interest is with the JPEG2000 algorithm [1]. A visual comparison of the CDBA and JPEG2000 is shown in Fig. 1 for the Baboon and Landscape images. The PSPNR (Peak Signal to Perceptual Noise Ratio) used here is the average of $PSPNR_i = 10log_{10}\left(255^2/WMSE_i\right)$, $i \in \{1,2,3\}$, where $WMSE_i$ is the Weighted MSE of color component i. It is given by $WMSE_i = \sum_{b=0}^{B-1} \eta_b G_b d_{bi} w_{bi}$ (cf. (12)). w_{bi} here is the perceptual weight for subband b of color component i based on the Contrast Sensitivity Function of the human eye. The PSNR (Peak Signal to Noise Ratio) used in this paper is $PSNR = 10log_{10}\left(255^2/MSE\right)$ using the mean MSE of (13).

As can be seen, for both images the CDBA scheme is superior to JPEG2000 that either introduces pronounced color artifacts (see Baboon: central frame) or shows loss of spatial details (see the side frames in Baboon and the frames in Landscape). We can conclude from this visual comparison that JPEG2000 allocates too few bits to the high frequency subbands compared to our scheme, which results in the loss of the details in these subbands. Also it does not divide the bit budget between the color components as efficiently as the CDBA, which causes color artifacts to appear. Additional comparisons for other commonly tested images show similar results. Both visually and quantitatively the CDBA scheme is superior to JPEG2000 with a gain of more than 2dB PSNR and approximately 3dB PSPNR, with comparable complexity [14]. Similarly, it can be shown that the CDBA is superior to the correlation and de-correlation methods being an optimized generalization of both.

6. SUMMARY

A new coding approach to color images using subband transforms has been proposed. This method, called CDBA, generalizes and optimizes both the de-correlation based and correlation based approaches to color image compression by using different CCTs at the subband level. In the process of its optimization we have found that the optimal choice for the color components transform is to use the KLT in each subband of the image. We have presented a new compression algorithm based on the CDBA method, compared it to JPEG2000, and have shown its superior performance both visually and quantitatively. This is due to better division of the bit budget between the color components and better energy compaction in the active subbands achieved by the CDBA. We conclude that the use of local CCTs is superior to the use of a global CCT, especially when based on the proposed R-D model.

[1]Implemented by the JasPer package that can be found at http://www.ece.uvic.ca/∼mdadams/jasper. It was run without tiling.

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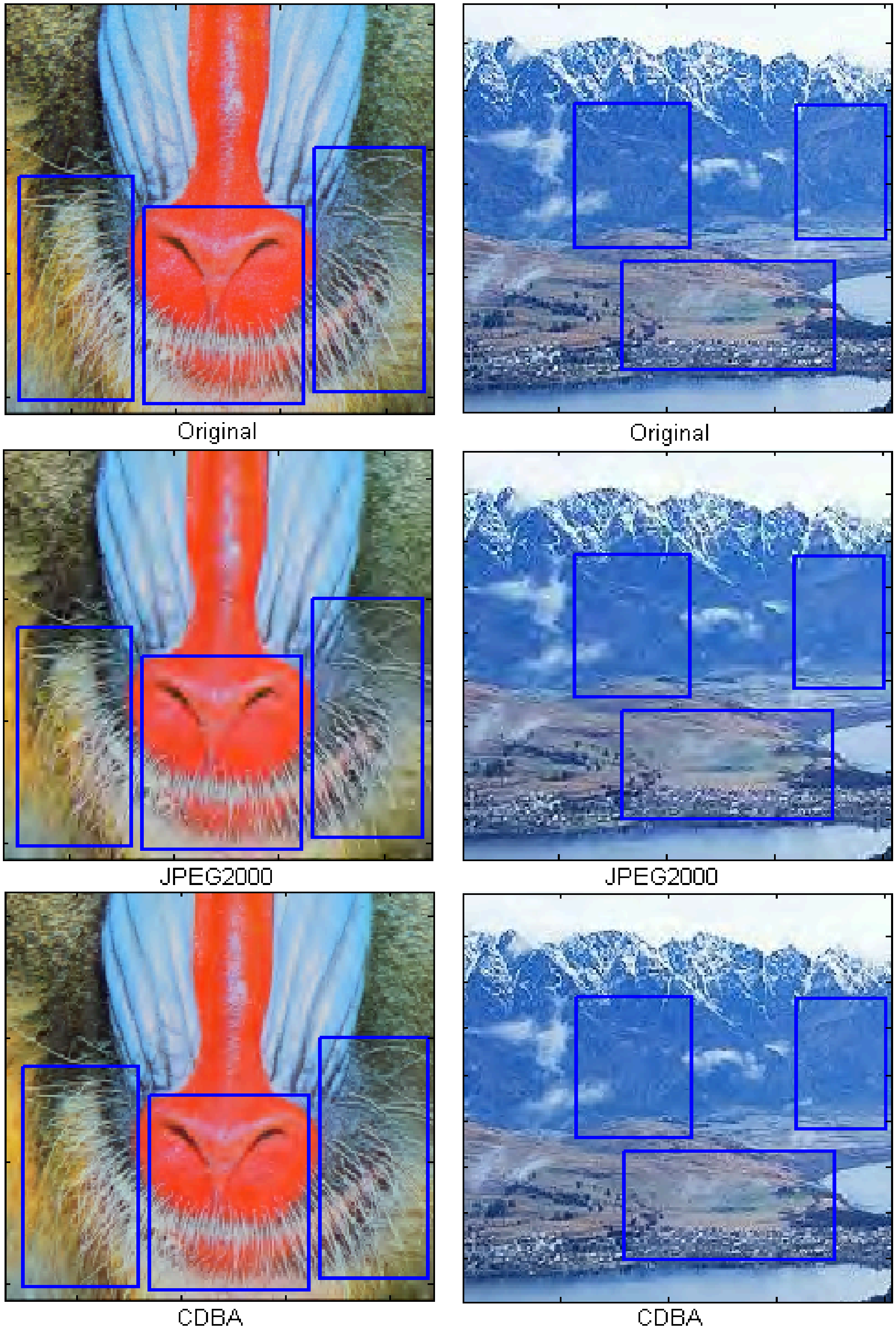

Figure 1: Baboon (zoomed in) at 0.98 bpp: original (top left), compressed by JPEG2000 (middle left, PSNR=26.0dB, PSPNR=36.1dB) and compressed by CDBA (bottom left, PSNR=30.0dB, PSPNR=40.1dB).
Landscape (zoomed in) at 1.27 bpp: original (top right), compressed by JPEG2000 (middle right, PSNR=27.0dB, PSPNR=37.8dB) and compressed by CDBA (bottom right, PSNR=31.2dB, PSPNR=41.7dB).