A Color Image Compression Scheme based on Psychovisual Criteria

F. Truchetet, O. Laligant, B. Joanne and L.F.C. Lew Yan Voon
Laboratoire LE2I, Université de Bourgogne
IUT, 12 rue de la Fonderie, 71200 Le Creusot, France

Abstract

We consider here the compression of still color image with very low distortion from the human eye point of view. The basic idea in this work is to take into account the variations of human eye/brain spatial resolution with color. The most natural way for an image processing researcher to perform such a scheme is to use a multiresolution analysis of the image to be coded before quantization and coding. Previous experiences connected with still grey value image compression/decompression scheme design have shown that the wavelet transform, Mallats algorithm is a very efficient method for this purpose, particularly if real time implementation is under consideration. Hence we present in this paper a wavelet transform algorithm for color image and we show how and with what performances the transformed image can be altered and reduced. We show that a quasi lossless compression/decompression scheme can be easily obtained with compression ratio up to 1:10 (quantization step was not considered here).The results obtained after a large series of tests based on psychovisual estimations rather than on pure PSNR evaluation are in good accordance with the assumed properties of the human visual perceptive system.

Introduction

We consider here the compression of still color image with very low distortion from the human eye point of view. The basic idea in this work is to take into account the variations of human eye/brain spatial resolution with color [1]. The most natural way for an image processing researcher to perform such a scheme is to use a multiresolution analysis of the image to be coded before quantization and coding. Previous experiences [2] connected with still grey value image compression/decompression scheme design have shown that the wavelet transform, Mallat algorithm [3], is a very efficient method for this purpose, particularly if real time implementation is under consideration [4]. Hence we present in this paper a wavelet transform algorithm for color image and we show how and with what performances the transformed image can be altered and reduced. In the first part we present the basic assumptions for human vision on which we have constructed our algorithm; the second part deals with the color transformation we used before applying wavelet transform and in the third part we show that a quasi lossless compression/decompression scheme can be easily obtained with compression ratio up to 1:10 (quantization step was not considered here). And finally we present the definition of a figure of merit for color image compression based upon results obtained in the previous sections.

Color Human Vision And Resolution

It is well-known that the retinal cells responsible for color vision are the cones and that there are three sorts of such cells each one being sensitive for a particular range of wavelengths: S-cone for the short ones (blue), M-cones for the medium ones (green) and L-cones for the longest (red). For artificial vision the same design is used and in color cameras there are three or sometimes four color channels. But while in these devices the number of pixels for each color is the same and they are regularly dispatched on the sensitive layer, in the eye the number of cells of each sort is very different and they are dispatched in a very irregular manner. So, spatial resolution depends on the considered retinal field and on color. Biological and behavioral measurements on cone mosaic lead to the conclusion that there are about twice as many L-cones as M-cones and that the number of S-cones is even smaller by several orders of magnitude [1][8]. But the brain is fed with more elaborated data than the basic three color information and we have to consider the preprocessing by the ganglion cells; studies in this field are still in progress and conclusions are not very steady but it seems that one can admit that there are three paths: one for achromatic information and two for chromatic contrast signals (red/green and blue/yellow)[6]. Another important idea to take into account is that the spatial resolution for line grids depends on the orientation of the lines and that vertically oriented details are seen with a better resolution than the horizontally oriented ones and these latter better than the diagonally oriented details. We will show in the next parts how we can take benefit from these properties to compress color images via multiresolution analysis.

Image Color Processing

A. Antagonistic colors model

In order to use a 1D scheme with color images we need to choose a projection of the 3D color space on three axes [5]. The usual RGB base does not correspond to color analysis done by the human visual system. A color space transformation is commonly used in color characterization which is called HSV transform (Hue, Saturation, Value). The non-linearity of this transformation is one of its drawbacks, another one is that it is not in good relation with human color representation. Psychovisual experiments tend to favor the base of antagonistic colors. The most know one is called hue-cancellation experiment, more information and bibliographic references can be found in [1]. In particular the ganglionic cells which form the last step of the preprocessing before transmission to the optical nerve make such a transformation. This base (H_1, H_2, H_3) *is* obtained by linear transformation of the RGB base. It is composed of an achromatic component (R+G) and of two chromatic ones (R-G and G-B). The transformation is more precisely defined in equations 1.

$$H = \begin{bmatrix} H_1 & = & \dfrac{R+G}{2} \\ H_2 & = & \dfrac{R-G}{2} \\ H_3 & = & \dfrac{2B-R-G}{2} \end{bmatrix}$$

As previously said this transformation is linear and easily invertible. H_1 component is supposed to be close to the one used by the brain (parvo-system and magnosystem) for analyzing contrast information. Parvosystem processes steady features and analyzes their shape and details. Magno-system processing deals with movement and 3D features [1]. H_2 and H_3 components underline antagonistic colors. H_2 is the $R-G$ component and H_3 *is* approximately the blue-yellow one. V_4 brain area uses H_2 and H_3 components in order to complete scene analyzing. Its resolution is three to four times lower than parvo-system and magno-system ones.

For these reasons and after some tries with other color bases we choose to use this transformation in our compression design.

B. Color image wavelet transform

The most popular algorithm for multiresolution image analysis by wavelet transform was proposed by S. Mallet [3], it allows, through orthogonal or biorthogonal projection, to decompose a grey value image into a set of detail images with size decreasing with resolutions in the three main directions (for separable filtering scheme). The last resolution level is not decomposed and the remaining information is contained in a small coarse << imaget >>. We have shown previously [4] that biorthogonal wavelet basis based upon B-spline function family leads to very efficient implementation design. It is, indeed, possible to perform real time (video rate) still-image transform with simple hardware set up involving only some FPGA circuits. This is due to the shortness of the filters and to the simplicity of their coefficients which can be expressed in the form of power of two.

The decomposition over the wavelet bases is obtained by applying the transform on each of the components H_1, H_2, H_3. We obtain thus a multiscale decomposition corresponding to the space-frequency resolution sensitivity of the visual system. In order to obtain a 2D transformation we use a separable scheme (more details can be found in [11]) which leads to creating for each resolution three wavelet components. Each component is dedicated to a particular orientation detail analysis. These three decomposition orientations (*v*: vertical, *h*: horizontal and *d*: diagonal) are particularly adapted since the visual system have different detection sensitivities according to the orientations of the pattern (the lowest being along the diagonal lines). We present below the principles of information suppression (rarely or not at all detected by the visual system).

Table 1. Scale pruning

j	o	$\mathbf{H}_i$	Flower	Mandrill	Lenna	
1	h	H_1	3	2	3	8
1	h	H_2	6	6	5	$\boxed{17}$
1	h	H_3	6	6	6	$\boxed{18}$
1	v	H_1	3	3	3	9
1	v	H_2	4	4	6	$\boxed{14}$
1	v	H_3	6	6	6	$\boxed{18}$
1	d	H_1	5	5	6	$\boxed{16}$
1	d	H_2	6	6	6	$\boxed{18}$
1	d	H_3	6	6	6	$\boxed{18}$
2	h	H_1	1	1	2	4
2	h	H_2	6	6	5	$\boxed{17}$
2	h	H_3	6	6	5	$\boxed{17}$
2	v	H_1	2	2	1	5
2	v	H_2	6	6	6	$\boxed{18}$
2	v	H_3	6	5	6	$\boxed{17}$
2	d	H_1	2	4	2	6
2	d	H_2	6	5	5	$\boxed{16}$
2	d	H_3	6	6	6	$\boxed{18}$
3	h	H_1	1	2	1	4
3	h	H_2	5	5	5	$\boxed{15}$
3	h	H_3	5	5	4	$\boxed{14}$
3	v	H_1	1	3	1	5
3	v	H_2	4	4	4	12
3	v	H_3	4	4	5	13
3	d	H_1	1	3	1	5
3	d	H_2	5	6	6	$\boxed{17}$
3	d	H_3	5	6	6	$\boxed{17}$

Compression Performance

In this paper we do not consider the quantization and the coding steps which are, naturally, important parts of any compression/decompression algorithm; some interesting elements for these stages can be found in [9] and [7]. We propose a study for preprocessing under the form of a << pruning >> of the wavelet coefficients, our aim being to maintain high visual quality for the reconstructed image. This << pruning >> is performed in two steps.

A. Scale pruning

In the first step we put to zero the blocks of wavelet coefficients corresponding to resolution and color contrast which are not proved to be essential from visual quality point of view. A color image contains indeed much more information than human brain usually exploits.

We choose to work on a three scales analysis. Going further in the analysis leads to underline details which are so blurred in original image that they are of no signification for human eye (the image being seen from distance in good accordance with its size). From wavelet coefficients obtained from the analysis we try to put to zero one set of coefficients belonging to one scale and one orientation. Then reconstruction is carried out and the reconstructed image is submitted to psychovisual appreciation. This experiment is repeated for each detail " imaget" of the set indexed by color axis (H_i), scale (j), and orientation (o), each index varying from 1 to 3. The psychovisual appreciation gives way to a quantized assessment on a scale ranking from 1 to 6. 1 is for a heavily degraded image, 3 corresponds to a good look image but with visible defects and 6 is reserved for an image with no perceptible differences from the original. Table 1 presents the results obtained for three typical images. The last column shows the global resulting assessment for each scale pruning try. We consider that every result upper than 13 (enclosed cases) is acceptable for a quasi-lossless compression scheme.

We can notice that all details corresponding to H_2 and H_3 (chromatic plane) can be suppressed; this is in good accordance to the assumed low resolution of the human visual system for colored components *(V^4* area) and to its high resolution for luminance contrasts. Only one block (a_d one) of H_1, the achromatic axis, can be omitted. It is a confirmation of the well known human lack of sensitivity to high spatial frequency components which are diagonally oriented. However it seems more difficult to conclude about comparative resolutions for color components H_2 and H_3.

The images presented below (figure 1) have been obtained after analyzing, pruning and reconstruction. Pruning was performed following the preceding conclusions so that all the unneeded blocks of wavelet coefficients are set to zero. Therefore, they correspond to a compression ratio of 1:4, and they were judged as 5 to 6 level quality in our psychovisual test.

B. Block thresholding

In the second step a thresholding is applied in each block of the remained coefficients. One threshold is chosen for each block in accordance with the dependance of visual resolution on the corresponding orientation of details [10], [12], [8], [1], [13].

We create frequency patterns by setting, in a given fictitious wavelet transform image, to an arbitrary value, saying x, the detail coefficients in one block, putting the other ones to zero and giving the same average value for all the pixels of the coarse approximation imaget (H_1 = 128, H_2 = 0, H_3 = 0). After reconstruction we obtain an image which is a frequency pattern for the chosen block (fixed by scale, orientation and color component). We measure the visual sensitivity to these frequency patterns by determining the minimum values of z which allow visual perception of each pattern.

Table 2 presents the results concerning thresholds found for frequency patterns detection. When the threshold is equal to zero, it means that wavelet coefficients belonging to this block must be preserved in the compression process because the eye is very sensitive to this frequency pattern. It is to be

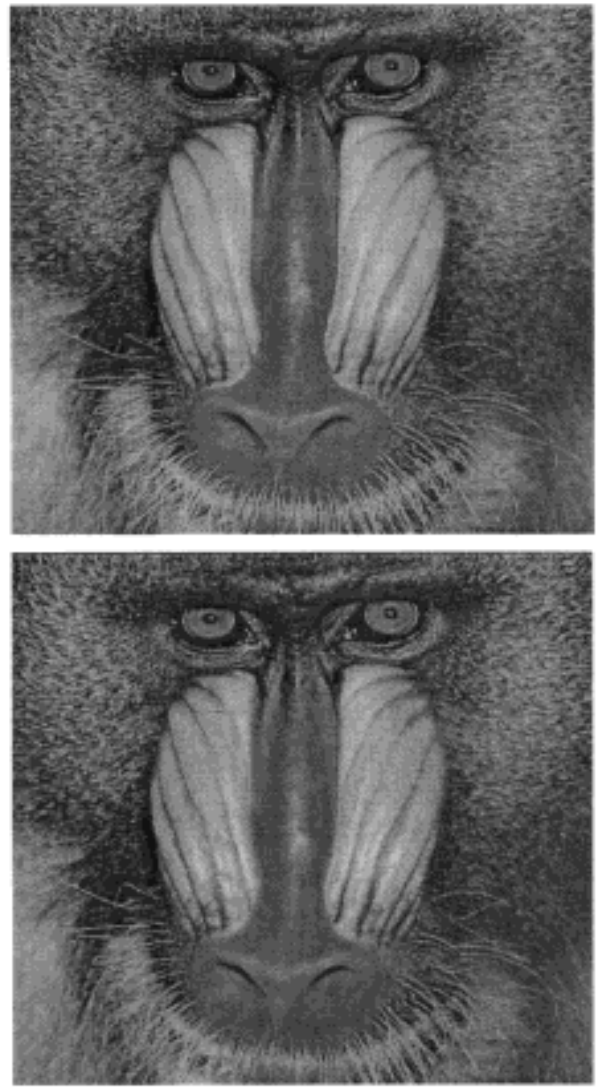

Figure 1 - Original image and image after analyzing, pruning and reconstruction. We can notice the slight blur.

Table 2. Thresholds for frequency patterns

Scale: *j*	**Orientation: *o***	**Threshold: *x***
1	H	2
1	V	5
2	H	0
2	V	0
2	D	1
3	H	0
3	V	0
3	D	0.2

Table 3. Compression ratio after pruning and thresholding

Images	**Size**	**Compression ratio**
Flower	368×350	1:11
Mandrill	512×480	1:6
Lenna	512×480	1:10

noticed that these results are quite consistent with presented assumption concerning spatial frequency sensitivity of human visual system. Indeed, on the one hands thresholds decrease with scale, this reflects a greater sensitivity for low spatial frequencies than for high ones. While, on the other hand, horizontal detail blocks are better detected than vertical detail blocks, themselves being more important than the diagonal ones. Block $j = 1$, $o = D$ is not tested because scale pruning has shown that it can be totally thresholded (i.e. set to zero).

Finally, we have applied the thresholdings on the remaining parts of the analyzed images after scale pruning. The reconstructed images obtained after such a treatment have been submit to our psychovisual test and the results sound good because the assessments where between 4 and 6.

In conclusion, the results obtained after a large series of tests based on psychovisual estimations rather than on pure PSNR evaluation are in good accordance with the assumed properties of the human visual perceptive system. The table 3 gives some examples of compression ratios obtained on our classical test images (see figure 2) for quasi-lossless compression.

Figure of Merit for Color Image Compression

During our psychovisual experiments we have noticed a very poor correlation between PSNR values and psychovisual assessments for color images. Typically some image judged as excellent has a PSNR of 25dB ! On the other hand we have noticed that the sensitivity of human vision to certain chromatic detail components is very low. Therefore we propose an estimation of the PSNR based upon pruned wavelets decomposition of the reconstructed H_1, H_2, H_3 images, the reference image being analyzed and pruned in the same way. The global PSNR is computed from quadratic errors between reconstructed and reference images, we only take into account the imagets which are relevant from human point of view. Such a selection is proposed which is based upon a large series of tries with a high quality requirement. The resulting criterium is denoted *FM;* it can be computed following the equation given below.

$$FM = 10\log_{10}(\lambda\Delta^2 \times \frac{1}{\sum_{i\in I_a}(x_i - \hat{x}_i)^2 + \sum_{n=1}^{3} 4^{n-1}\sum_{o\in O}\alpha_n^o \sum_{i\in I_n^o}(x_i - \hat{x}_i)^2}$$

$$\text{with}\begin{cases} \Delta : \text{transform range} \\ \lambda = T + \sum_{n=1}^{3}\sum_{o\in O}\alpha_n^o T \\ I_\alpha : \text{course imaget pixels} \\ \mathrm{I}_n^o : \text{detail imaget pixels for orientation } o \\ \alpha_n^o \in [0,1] \\ T : \text{image size} \end{cases}$$

Figure 2 - Original image and image after analysing, pruning, block thresholding and reconstruction. The compression ratio is 1:10.

The coefficients α_n^o are chosen in accordance to the psychovisual assessments A_n^o previously obtained:

$$\alpha_n^o = \frac{A_n^o}{18}$$

The results seem to be promising but they have to be assessed on various color image compression schemes.

Conclusion

This study is the first stage of a complete approach of the compression problem of still color image with good visual restitution. The results already obtained are consistent with the known features of human vision characteristics and they show that the multiresolution analysis provided by wavelet transform on a well cho sen color space is a good way to take into account the dependency of the resolution on the color contrast and on the detail orientation. This multiresolution analysis gives way to a quantized criterium for color image com pression scheme taking into account the human vision characteristics .

References

[1] B. A. Wandell, << Foundations of Vision >>, Sinauer Associates, Sunderland, 1995.

[2] M. Antonini, M.Barlaud, P. Mathieu, I. Daubechies, << Image coding using wavelet transform >>, IEEE Trans. on Image Processing, vol.1, N°2, pp. 205-220, April 1992.

[3] S. Mallat, << A theory for multiresolution signal decomposition; the wavelet representation >>, IEEE trans. on PAMI, vol. 11, N° 7, pp. 674-693, July 1989.

[4] F. Truchetet, A. Forys, << Implementation of still-image compression-decompression scheme on FPGA circuits >>, Still image compression, SPIE, vol. 2669, pp. 66-75, San Jose, Jan. 1996.

[5] L. Brun, J. P. Braquelaire, << Une amelioration des methodes de quantification de couleurs par partition dynamique >>, 2eme journees AFIG, Toulouse, France, 1994.

[6] A. Gottshalk, G. Buchbaum, << Information theoretic aspects of color signal processing in the visual system >>, IEEE SMC, vol. 13, N°5, pp. 864-873, 1983.

[7] I.K. Eom, H.S. Kim, K.S. Son,, << Image coding using wavelet transform and human visual system >>, Still-image compression, SPIE, vol. 2418, pp. 176-183, San Jose, 1995.

[8] S.A. Raj ala, H. J . Trussell, B. Krishnakumar, <<Visual sensitivity to color-varying stimuli >>, SPIE, vol. 1666, pp. 375-386, 1992.

[9] S.A. Rajala, << Impact of human visual perception of color on very low bit-rate image coding >>, SPIE, vol. 2308, pp. 39-46, 1994.

[10] H.R. Wilson, D. Regan, << Spatial-frequency adaptation and grating discrimination: predictions of a line-element model >>, Journal of the Optical Society of America, Vol. 1, pp. 1091-1096, 1984.

[11] M. Vetterli, J. Kovacevic, << Wavelets and Subband Coding >>, Prentice Hall, Englewood Cliffs, NJ, 1995.

[12] J. M. Foley, G. E. Legge, "Contrast detection and near-threshold discrimination in human vision", Vision Res., vol 21, pp. 1041-1053, 1981.

[13] N. Graham, J. Nachmias, "Detection of grating patterns containing two spatial frequencies: A comparison of single-channel and multiple-channel model", Vision Res., vol 11, pp. 251-259, 1971.