QUALITY ESTIMATION IN WAVELET IMAGE CODING

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ABSTRACT

The wavelet transform is a very powerful tool for image coding for which the quality of the compression is depending on the choice of the filter banks associated to the wavelet. These filters can be characterized by two indices: a spatial index related to their significant support and a frequency index related to their aliasing.

This work explores the connection between a quality criteria and these two indices for a given image family. Two useful applications are presented: in the first one a neural network allows us to deduce the best filter bank for a given image. In the second one a quality criterion for a new image is estimated knowing the filter bank.

1. INTRODUCTION

In compression schemes, the Discrete Wavelet Transform (DWT), used in standard JPEG2000, allows important compression ratios without artifacts (blocks effect) as observed in the Discrete Cosine Transform (DCT).

In the Wavelet Transformation (WT) the choice of the associated filter bank is very important and directly related to the efficiency of the compression. Both the coding algorithm and the evaluation of the compression quality are computationally heavy, thus we have to cape with a still opened question: for a selected filter bank, is it possible to predict the compression quality? In other words: is it possible to estimate a quality criterion without making the compression by itself?

Our study is based on a former work [1] for which two indices characterize a filter bank: a frequency index I_f and a spatial index I_s. Here, the relation between I_s, I_f and quality criteria of compression is explored, then a Radial Basis Neural Network (RBNN) is implemented to predict this quality either for a new filter bank or for a new image.

This paper is organized as follows: in section 2 the basic compression scheme is briefly remained as well as criteria of coding performance. In section 3, the prediction of compression quality is related to spatial and frequency indices and is approximated with the RBNN. Section 4 is dedicated to applications wherein a RBNN is used as a predictor. Section 5 summarizes our remarks and suggests future research direction and improvements.

2. COMPRESSION SCHEME

2.1 Description of the compression scheme

The traditional diagram of image coding by DWT consists of three basic steps (Fig. 1).

- The DWT decorrelates information in the original image leading to a new form of information supporting a more efficient compression.
- The quantization step of the DWT coefficients restricts them into a limited series of values *i.e.* removes information considered to be useless. Thus this process is an irreversible one.
- The entropy-coding step assigns to each quantified coefficients a code as shorter as possible. Then the total available budget of bits should be distributed on the different subbands of the image according to the specified compression ratio. This procedure is called bits allocation; and literature gives various approaches to solve this problem [2, 3],…

The image decompression follows an inverse procedure. For each step above, the selected algorithm is very important and has an effect on coding quality, in this study we restrict our interest to the first step.

2.2 Estimation of the compression quality

When an irreversible image compression method is applied, it becomes useful to measure its performance in order to optimize it. Numerous papers introduce various objective and subjective metrics; our work deals with the following criteria:

- The Root Mean Square Error RMSE (equation (1)) defined between the original image pixels *I(m, n)* and decompressed image pixels *Î(m, n)* with $(0 \le M \le m\text{-}1,\ 0 \le N \le n\text{-}1)$.
- The Peak Signal to Noise Ratio PSNR given by equation (2) where 2^R-1 is the maximum gray level number.

$$RMSE = \sqrt{\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}((I(m,n)-\hat{I}(m,n))^2} \quad (1)$$

$$PSNR = 10\log_{10}\frac{(2^R-1)^2}{MSE}\,db = 20\log_{10}\frac{2^R-1}{RMSE}\,db \quad (2)$$

When the original and the decompressed images are identical, the MSE is null while the PSNR tends towards infinity. In most cases, a PSNR greater than 30 db is considered as leading to a correctly reconstructed image.

3. COMPRESSION QUALITY PREDICTION

The prediction of the compression quality is not sufficiently evoked in the literature; even so it is of capital interest in the dynamic coding schemes for which an adapted coding algorithm is dynamically selected from a set of predefined algorithms. This selection is computationally heavy,

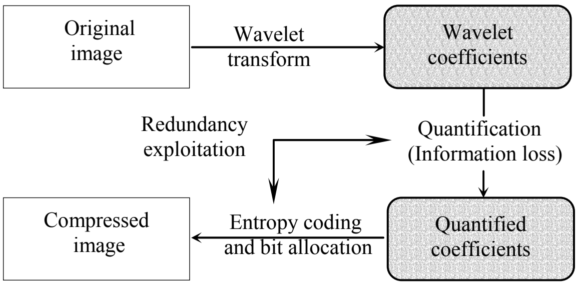

Figure 1: Basic compression scheme

since the evaluation of the coding quality is an expensive operation, which requires performing coding, decoding, then comparison between original and decompressed image. Thus it is interesting to predict the compression quality without performing the compression by itself.

3.1 Choice of wavelet basis for compression

Several criteria influence strongly wavelet basis performances for image coding: vanishing moments number of the mother wavelet, mother wavelet regularity, phase linearity of the associated filters, size of filters support… Some of these criteria are mutually inconsistent and cannot be found in the same wavelet, thus many recent works [5-8] tried to identify the wavelet basis which optimizes the best combination of these criteria. In our approach the performances of the filters are globally characterized with two indices as defined below.

3.2 Indices I_s and I_f

The filter bank of a wavelet consists of a low-pass filter *h* and a high-pass filter *g*. For the needs of this current work, it is characterized by two indices:

Spatial index $$I_S = \sum_{k=0}^{\infty} \left|h * g[k]\right| k^2 \quad (3)$$

Frequency index $$I_f = \int_0^{\pi} \left|G(\omega)H(\omega)\right| d\omega \quad (4)$$

The spatial index is inspired by the variance formula, which measures data dispersion around the average value. It characterizes the filter bank in the spatial domain from the significant support of the convolution of the low-pass and high-pass filters. When the wavelet order is incremented, the size of the significant support of the convolution increases and so does the spatial index.

The frequency index of the filter bank is related to the measure of the aliasing of the two filters *h* and *g* due to the overlapping of their frequency responses. We define the overlapping area as the surface delimited under the intersection of the two frequency response curves of the filters. The error surface is the difference between the frequency index and the overlapping area (Fig. 2).

With orthogonal wavelets, I_f fits nearly the overlapping area. When the wavelet order is incremented, this area decreases and so does the frequency index (Fig. 2 a, b). Furthermore, decomposition ($\overline{h}$, $\overline{g}$) and reconstruction *(h, g)* filters verify the relations: $\overline{h}(n) = h(-n)$ and $\overline{g}(n) = g(-n)$ thus their frequency responses and consequently their frequency indices are the same.

In the biorthogonal case, the surface error is greater than for the orthogonal one. I_f varies always like the wavelet order. Decomposition and reconstruction filters have symmetrical frequency responses around $\pi/2$. Hence their overlapping areas are the same but their localizations are symmetrical around $\pi/2$ consequently the frequency indices of the decomposition ($\overline{h}$, $\overline{g}$) and reconstruction filters ($\tilde{h}$, $\tilde{g}$) are identical. Fig. 2 c, d shows an example of a biorthogonal Bspline wavelet.

A good filter bank must be efficient simultaneously in the spatial and frequency domains, this means that the quality of the filter bank is a trade-off between its spatial and frequency quality.

3.3 Relation between I_s, I_f, and quality criteria

A filter leads to a unique point in the "I_f" versus "I_s" plan. For a given wavelet family the $I_s = f(I_f)$ graph is monotonous, when the spatial index increases, the frequency one decreases (Fig. 3). The interest of WT is its spatial and frequency simultaneous ability of analyzing information, so it must ensure a better trade-off between a spatial and frequency analysis. This compromise is obtained when the current point is the more closer to the origin of the plan. In fact an experimental verification in which some images are compressed and decompressed by wavelet filters located at different positions in the (I_f, I_s) plan shows that: when the I_s index is high and I_f is low (for example db40) compression with the associated filter give a blur effect on the decompressed images, when the I_s index is low and I_f is high (for example db1) compression with the associated filter give a blocs effect on the decompressed images and the better compromise between the two effects is obtained when the filter is closer to the origin (Fig. 4). These results show that the selected indices characterize different parameters of the compression quality and this quality is depending on both indices. Quality criteria can be predicted by means of a RBNN as developed in section 4.

4. APPLICATIONS

4.1 Coding software

The software of image coding for our purpose is the "Wavelet transform-based image coder for greyscale images" available on [9]. It is a simple coder designed for experimentations but quite effective and modular. Each elementary component is selected for high performances and can be replaced by our own component.

We implemented several wavelets filters: Daubechies, Symlets and Bsplines in the wavelet coder. Compression performances tests for two different images: the Barbara image and a texture image (Fig. 5), allow us the following and trivial observations:

- The RMSE increases as the PSNR decreases when the compression ratio decreases.
- For the same ratio, the Barbara image admits a better quality after decoding than a texture image since the texture images contain many details that correspond to high frequencies. The algorithm of WT coding allocates more bits to the low frequencies areas, for which human eye is more sensitive, thus after decoding the high frequencies images have a low PSNR.
- It is noticeable that the quality of compression depends also on the image class (medicals, naturals, or texture images).

4.2 First application

For a given set of filter banks, knowing the coding performances of an image class, the goal is to estimate the coding performances for a new filter bank and for a new image owing to the same image class.

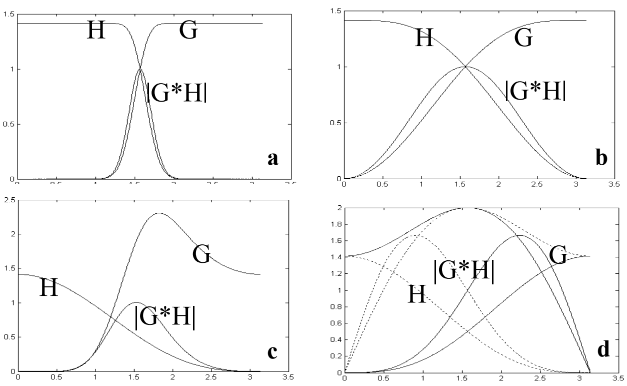

Figure 2: Filter banks frequency responses; **a**: Daubechies 40 (db40), **b**: db2, **c**: Bspline3.9 (bior3.9), **d**: bior3.1 (solid lines refer to decomposition filters, dashed lines to reconstruction filters).

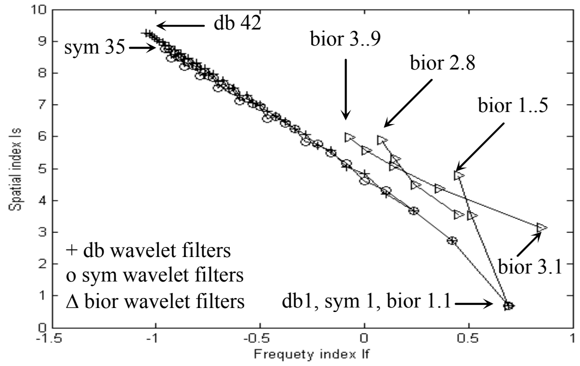

Figure 3: I_s=$f(I_f)$ for bior 1.1…bior 3.9; db1…db42; and symlets (sym) sym1,…sym35, in log abscises.

The criteria PSNR, RMSE with respect to I_s, and I_f were fitted by a RBNN for the Barbara image with 4:1 compression ratio; the choice of the neural network is justified by its interesting interpolation and approximation properties.

After training, this neural network becomes a predictor of the coding performances. Thus, both the coding algorithm and the calculation of the quality criterion behave as a black box, the indices of the filter bank I_s and I_f are the inputs, while the outputs are the predicted quality criteria according to selected metrics (Fig. 6).

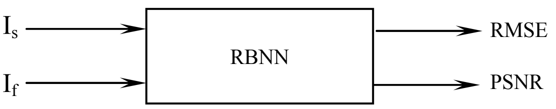

Figure 6: RBNN coder.

For each 20 Symlets filter banks, the real values of quality criteria are calculated and compared to their estimated value as shown in Fig. 6, their highest difference as well as their RMSE are given in Table 1 confirming the predicting ability of the neural network.

	Criterion RMSE	Criterion PSNR
Max error	0.1218	0.4678
$\sqrt{MSE}$	0.0041	0.0582

Table 1: Coding performances (application 1)

This approach is an efficient method for measuring the performances of other filter banks close to already known filter banks, either by interpolating the criterion curves or thanks to the RBNN with I_s and I_f as entries.

Figure 4: Coding performances for Barbara image and Daubechies wavelet filters; **a**: db1, **b**:db7, **c**:db40

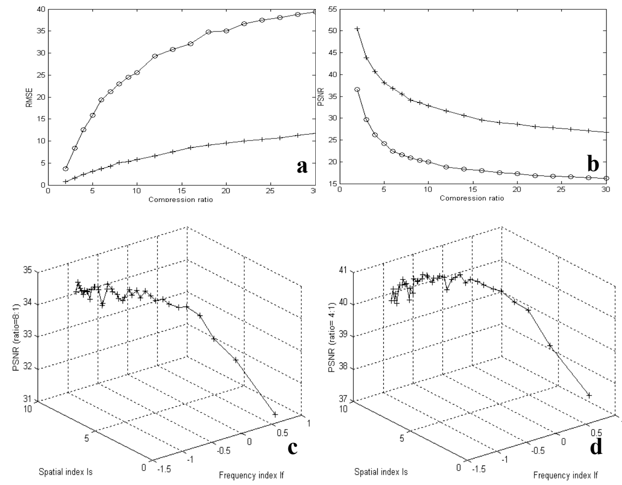

Figure 5: Coding performances: **a, b** RMSE and PSNR with respect to compression ratio, (o: Barbara image, +: texture image), **c, d**: PSNR with respect to indices for Barbara image, Daubechies wavelet filters and two different compression ratios (on left 8:1, on right 4:1).

4.3 Second application

Let suppose that coding performances for one or several filter banks are known for a set of images; the goal is now to predict the coding performances for a new image. This problem can be posed differently: let being a given image; which filter bank provides the best compression quality for this image?

To deal with this problem a set of 25 texture images, 512x512x8 bit grayscale, is selected from the USC-SIPI data base [10]. Texture groups are relatively different such as the standard deviation is 5.95 for the PSNR. The average criteria (PSNR, RMSE) obtained on the 25 images and for 40 Daubechies filter banks, are plotted with respect to I_s and I_f in Fig. 7, as well as the estimated mean average criteria provided by the RBNN predictor (Table 2). Real and estimated criteria are nearly superimposed (Fig. 8).

	Criterion RMSE	Criterion PSNR
Max error	0.0001	0.021
$\sqrt{MSE}$	0.0000	0.0000

Table 2: Coding performances (application 2, training basis)

After training, any new image provides the same quality for a selected filter bank

Two images were selected, the first one presents few differences compared to the average of the 25 images, on the contrary the second image has many differences. The real PSNR with 40 Daubechies filter banks is computed and plotted in Fig. 9 for the first image and in Fig. 10 for the second one.

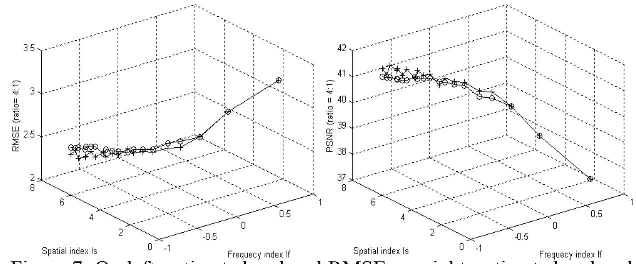

Figure 7: On left, estimated and real RMSE; on right, estimated and real PSNR (+: real curves, o: estimated curves), for 4:1 compression ratio and Symlet wavelet filter banks.

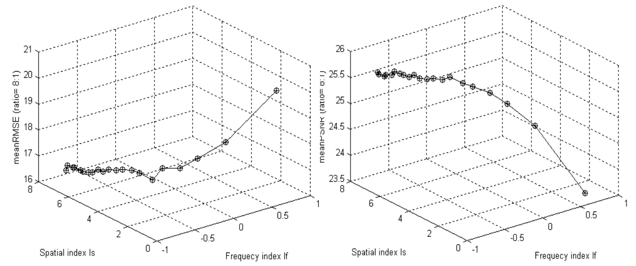

Figure 8: On left, estimated and real mean RMSE; on right, estimated and real mean PSNR (+: real curves, o: estimated curves), for 25 images, 8:1 compression ratio and Daubechies wavelets.

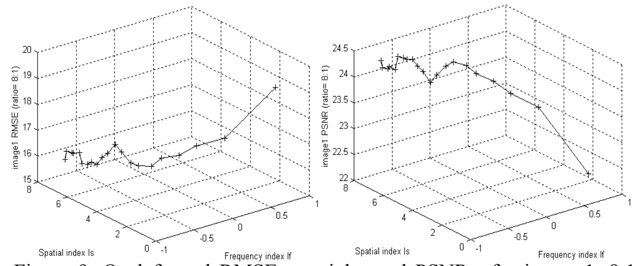

Figure 9: On left, real RMSE; on right, real PSNR, for image 1, 8:1 compression ratio, and Daubechies wavelet filter banks.

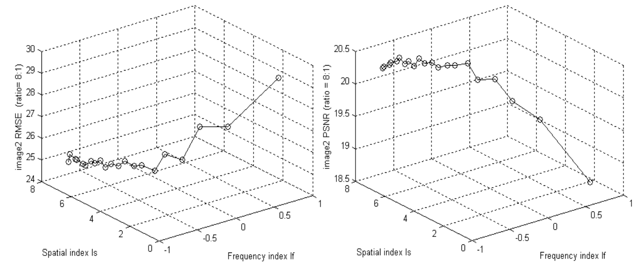

Figure 10: On left, real RMSE; on right, real PSNR curves, for image 2, 8:1 compression ratio, and Daubechies wavelets.

As expected, the error of the quality criterion for the second image is greater than the one of the first image. Comparison between the real and the estimated values (Table 3) for both images confirms that the training database must be chosen very carefully. In that case, the results are very satisfying.

	Image 1		***Image 2***	
	Criterion RMSE	Criterion PSNR	Criterion RMSE	Criterion PSNR
Max error	0.8568	1.5749	0.056	0.2745
$\sqrt{MSE}$	0.5713	1.2971	0.0081	0.0958

Table 3: Coding performances (application 2, two images comparison)

5. DISCUSSION

The framework of this study is the estimation of criteria for evaluating the compression quality in image processing. Filter banks of a DWT can be characterized by two indices defined in the spatial and frequency domains that are also related to the compression ratio, to the image family and to quality criteria of compression. Experimental quality criteria were calculated, then were approximated by a radial basis neural network in order to predict the compression quality for either new filter banks or new images with consistent results. Thus the coding algorithm and the estimation of the quality are considered as a black box, the filter banks indices are the inputs, the selected criteria of the quality such as RMSE or PSNR are the outputs. Now it is useful to extend this work to more wavelet transforms and more image families representative of any current application with different compression ratios.

Quality criteria such as PSNR allow us to evaluate the numerical difference between images, however they do not reflect accurately the appreciation of the humane eye, thus it is interesting to integrate other quality criteria, such as those based on the modeling of the human vision system.

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