Application of Entropy-Constrained Vector Quantization to Subband Images

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Abstract: Vector quantization is a powerful way to compress images, rarely used in present compression schemes. We present here the use of this technique on subband images, by means on an entropy contrained quantization algorithm. The codebooks are predetermined on a set of images to speed up transmission. The outline of the method is presented, as well as some experimental results.

1. Introduction

Vector quantization (VQ) is a powerful lossy compression scheme for image coding, but it exhibits two drawbacks. First, when applied directly to the original image, it frequently leads to poor results; one way to overcome this problem is to couple it with subband decomposition as a pyramidal multi-resolution decomposition algorithm[0]. Indeed, spanning an image onto several resolution levels yields subimages whose statistical properties are better conditioned than the original image ones.

The second problem is related to the size of the codebooks that have to be transmitted. To overcome it, we have experimented the use of predetermined codebooks for every subband. These sub-codebooks are created using ECVQ quantization working on a training set comprised of vectors belonging to different images. Each subcodebook contains few reproduction vectors. The whole set of subcodebooks exhibits a lower distortion than a codebook computed over the original image.

Section 2 presents the coding method. Experimental results of compression performances are detailled in section 3.

2. Outline of the CODEC

Figure 2 describes the outline of the coding method. Images are decomposed in wavelets and every subband is coded thanks to a a specific code book. As usual in wavelet transforms, we will call the subbands at first layer LH, HL, HH and LL, and the decomposition of this band on the first layer LLLH, LLHL, LLHH and LLLL, etc; the corresponding codebooks will be given the same name. These codebooks are obtained, in a learning phase, by analysing concurrently a set of representative images 256×256 pixels using ECVQ algorithm (figure 1).

These predefined sub-codebooks are used for the quantization the sub-bands of image obtained by pyramidal scheme using the 2-D wavelet transform,, illustrated by figure 2. The depth of multiresolution decomposition is fixed to 3, using a biorthogonal wavelet filter set of 10-tap length (biorth 4.4).

Figure 3 show the histogram of the wavelet coefficients on LENA image. The sub-band corresponding to the low frequencies (LLLLLL) is keep unquantized and it is the coarse image of the original image. By examining, the histogram of high frequency sub-bands (LH, HL, HH, LLLH, LLHL , LLHH, LLLLLH, LLLLHL , LLLLHH), there is a large number of small coefficients and a few signifiants coefficients.

The small ones correspond to smooth regions in sub-bands and the larges ones to edges and texture. These significant coefficients are an important part of the image, and we want to preserve it. Since this coefficients correspond to infrequent events we propose ECVQ algorithm to quantize them. This algorithm associates a low distorsion for blocks which have a lower probability of occurance[0] and we can obtain low bit rate. In order to reduce the number of bits, a lossless compression technique such as Huffman coding is applied to the coded coefficients

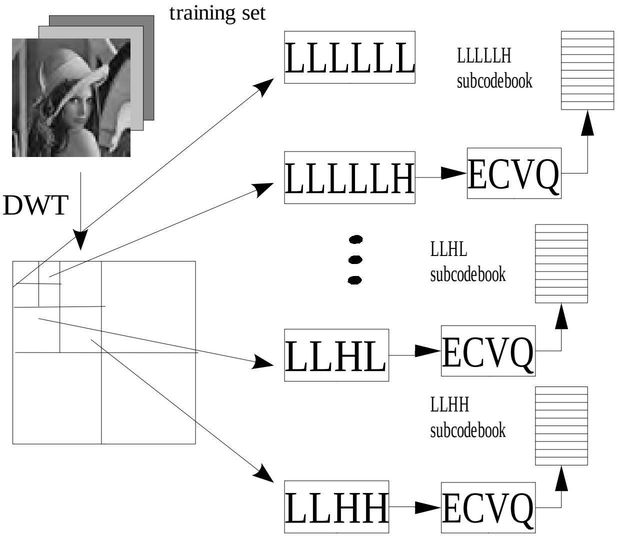

Fig.1: The principe of generation the commun sub-codebooks.

3. *ECVQ algorithm principle*

The ECVQ algorithm is a generalisation of the LGB algorithm [*0*]. It allows the design of vector quantizers with minimum rate distortion by imposing a constraint on the entropy. The problem then consists to find a set of reproduction vectors which minimize the following lagrangian:

$$J = D + \lambda \times H$$

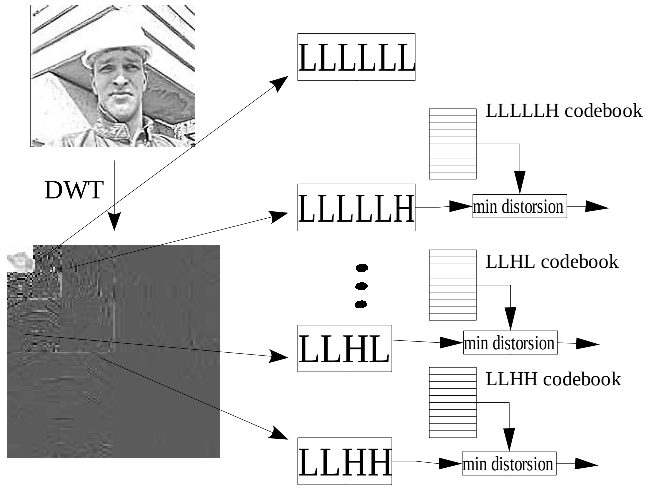

Fig. 2: Subband images coding scheme

D being the average distortion and H the entropy.

1. Initialization Define an initial reproduction codebook by means of the LGB algorithm. Determine the probability p_i of every codeword i. Set t=0, and $J^{(t=0)} = \infty$
2. Assign each input vector X in the training sequence to its nearest reproduction $\hat{X}$, where the metric used is $\rho(X, \hat{X}_i) - \lambda \times \log_2 p_i$. This corresponds to the original distortion measure ρ biased by negative λ log of the probability of the i^{th} codeword (entropy).
3. Update the estimate of the probability of the i^{th} codeword.
4. Move each reproduction to the centroid of all input vectors that were assigned to it.
5. If $(J^{(t)} - J^{(t+1)}) > \varepsilon$

   set t=t+1 and go to step 2

   Else you' re done.

After convergence, the codebook achieves a minimum of the lagrangian. When λ is high, the lagrangian is significantly penalized by codebook entropy H, and the optimal solution is a codebook with relatively high distortion. When λ is low, the optimal solution is a codebook relatively an high entropy and a relatively low distortion. In particular, two points are easy to find. The first is when λ =0; no penalty is assessed on the codebook entropy, and the ECVQ algorithm reduces to the generalized Lloyds algorithm. The second point is for large values of λ . This point corresponds to the rate zero, and the codebook is composed of a unique vector that is the centroid of the entire distribution.

To obtain the value of λ that matches a target value of R, say R_{target}, let apply the following steps:

- Set (R_{low},D_{low}) to be the rate and distortion when using a rate-zero quantizer.
- Set (R_{high},D_{high}) be the corresponding rate and distortion using a quantizer with λ =0.
- Set λ to the slope of the line between these two points, i.e. λ_{next} =(D_{low} – D_{high})/(R_{high} – R_{low})

Use the ECVQ algorithm with this λ to find a quantizer with an average rate and distortion equal to (R_mid,D_mid), where R_mid is somewhere between R_low and R_high.

If R_mid is close enough to R_target, then you're done.

Else if R_target is between R_low and R_mid, then set (R_high,D_high) = (R_mid,R_mid), and goto step 3.

Else if R_target is between R_mid and R_high, set (R_low,D_low)= (R_mid,R_mid), and goto step 3.

The important gain in this algorithm is that it reduces considerably the large number of codewords that the LGB algorithme makes in the initial state, while insuring a low bit rate

4. Experimental results

Level 1 contains 75% of the coefficients, and it is critical to the total compression ratio. According to that its impact has drawn special attention[*0*], yielding the conclusion that the coefficients in level 1 are not necessary.

We used the commun sub-codebooks generated by the ECVQ algorithm that has been presented in the previous section on quantization. Table 1 summarizes the results, were N is the number of codewords in the sub-codebook that respect the nearest-neighbor rule, for the input vector in sub-band, and k the length of each vector for each shape and level.

The compression achieved is described in three columns: the entropy, the compression without using huffman coding, and the compression after applying the huffman coding.

Several images were trained together to create commun sub-codebooks. These images, which were part of the training sequence, were restored using the commun sub-codebooks.

The results displayed in figure 4, show clearly that edge definition is enhanced but a losses occur in smooth region. We finally achieved a low bit rate of 0.1802, and a compression ratio of 44.39.

The commun sub-codebooks created by ECVQ algorithm are used for compression of the images outside the training sequence, we have obtained 0.2109 bpp and a compression rate of 37.93 . The results are shown in figure 5.

The total average bitrate is calculated using the following formula :

$$R_T = R_{app} + \sum_{l=1}^{J} \sum_{s=(H,V,D)} (R_{l,s} / 2^{2\times j})$$

where :

R_{app} : is the average bit rate of LL band in level 3.

$R_{l,s}$: is the average of LH, HL, HH sub-bands of level 2 or 3 and shape s

5.Conclusion

In this paper, we have developed a simple and fast image coding scheme combining the wavelet transform and the use of the ECVQ method for compression. The results obtained, show an compression rate between 38-44, with a low bit rate.

6.References

[1]. M.Barlaud, P.Mathieu & M.Antonini: "wavelet transform image coding using vector quantization" in Proc.6th workshop MDSP, Montery CA, sept.1989.

[2]. P.A. Chou, T. Lookabaugh & R. M.Gray: "Entropy contrained vector quantization", IEEE trans. on ASSP, vol.37,1, pp.31-42, 1989.

[3]. Y.Linde, A. Buzo & R.M. Gray: "An algorithm for vector quantizer design",

IEEE trans. on comm., vol.COM-28, No.1,pp.84-95, January 1980.

[4]. A.Averbuch, D. Lazar & M. Israel: "Image compression using wavelet transform and multi- resolution decomposition", IEEE trans. on image proc., Vol.5, No 1, January 1996

LEVEL	*SHAPE*	*lambda*	*N*	*K*	*bPP*		
					entropy	*huffman*	*Without huff*
2	*Horizontal*	λ *=1301.1972*	*32*	*16*	*0.0625*	*0.1104*	*0.3125*
3		λ *=2192.2091*	*20*	*4*	*0,271484*	*0.4258*	*1.08048*
2	*Vertical*	λ *=2033.8701*	*68*	*16*	*0.14941*	*0.1812*	*0.3804*
3		λ *=3961.5757*	*30*	*4*	*0.53027*	*0.6924*	*1.22672*
2	*Diagonal*	λ *=468.79447*	*64*	*16*	*0.13720*	*0.1697*	*0.375*
3		λ *=709.94064*	*44*	*4*	*0.584961*	*0.7295*	*1.36485*

Table 1 : Results of the quantization the subbands of LENA

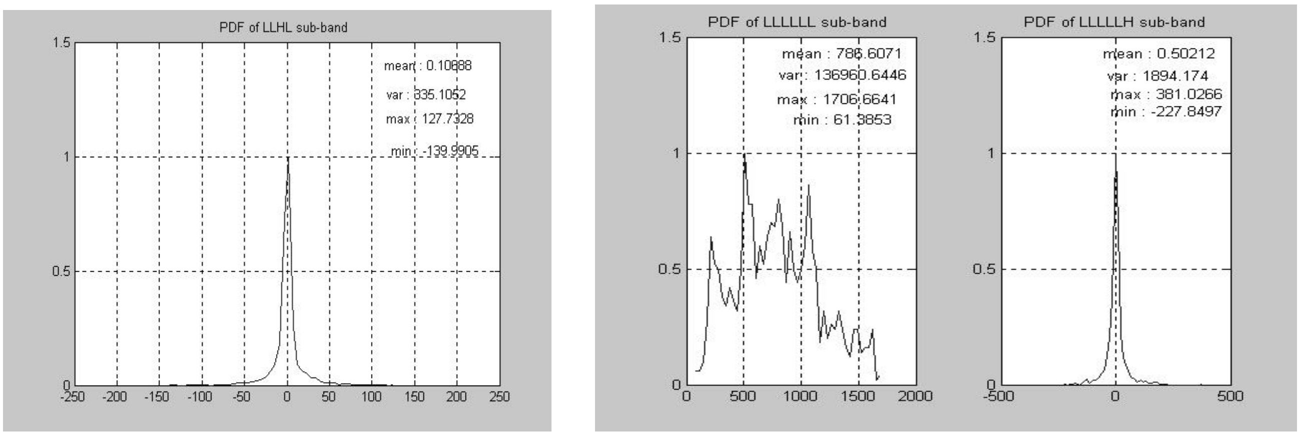

Fig. 3 : Histogram of sub-bands of Lena

Fig. 4 : Restoring images into the training set LENA with 0.1827 bpp and PSNR=28.96 cameraman with 0.1802 bpp and PSNR=30.49

Fig. 5 restoring image outside the training set TREE with 0.2109 bpp and PSNR=24. 52