

IMAGE CODING USING VECTOR QUANTIZATION AND DECOMPOSITION INTO 10 SUBBANDS

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Abstract. In this paper, the decomposition of the image into 10 subbands is realized. The image is decomposed rowwise first, and columnwise afterwards, giving four subbands. Then, the lowest subband is two times recursively decomposed rowwise and columnwise giving additional seven subbands. The coding of subbands is realized as follows: the lowest subband is scalar quantized into 256 levels, and the other subbands are vector quantized using 2×2 or 4×4 blocks. For each subband, which correspond to the some specific orientation of the image, the code table is constructed. The length of code table is 16, for the higher subbands, and up to 256, for lower subband. These code tables are optimized using training set of many different images. The test image "Lena" is not contained in the training set, hence, the code tables do not increase the entropy of the coded test image. The experimental results show that the subjective quality of the image is very good, at the first order entropy of about 0.33 bpp and PSNR of 29 dB.

Key words: Image coding, vector quantization, image decomposition, code table, Lena, filter, quadrature mirror filter, PSNR.

1. Introduction

The basic idea of subband coding of images is to decompose image into subbands, and to encode each subband separately using a coder and bit rate appropriate to the statistics of that subband [10]. To obtain further entropy reduction, vector quantization is used in this work. For each subband, corresponding to some orientation of the image, separate codebook is constructed. In this way, The distortion, introduced to some orientation

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of the image, separate codebook is constructed. In this way, the distortion, introduced through vector quantization, is reduced. The codebooks were constructed and optimized using training set of many different images. Experimental results are given for a image not contained in the training set.

2. Subband decomposition using QM filters

It is possible to decompose an image into subbands using nonseparable or separable two-dimensional filters, as illustrated in Figs. 1 and 2. General two-dimensional subband system, using nonseparable filters is shown in Fig. 1.

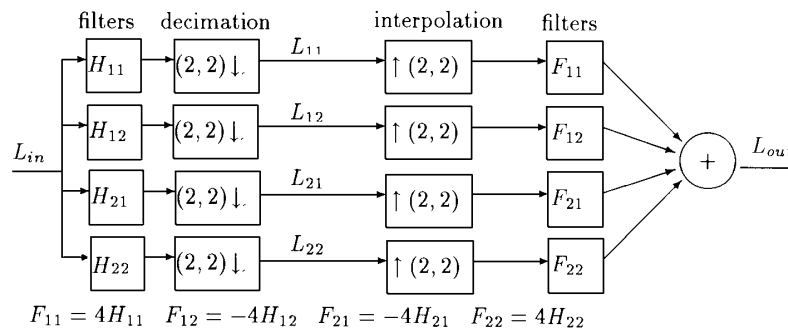


Fig. 1. General two-dimensional system for subband analysis and synthesis

Figure 2 shows special case of separable row and column filtering, applicable in the case when it is possible to represent frequency characteristics of two-dimensional filter as a product of frequency characteristics of two one-dimensional filters.

The use of nonseparable filters has the advantage that the subband analysis may have directional properties not constrained to horizontal and vertical directions, and nonrectangular subsampling patterns can be used [4]. Nonseparable filters can have better frequency characteristics due to the fact that nonseparable impulse response with $M \times M$ coefficients has M^2 free variables, while its separable counterpart has only $2M$ free parameters [4].

In spite of all advantages of nonseparable filters, much lower complexity of realization of separable filters compared to the nonseparable filters (count

of arithmetic operations [9]) is usually the deciding factor in favor of using of one-dimensional filters. Rowwise and columnwise one-dimensional filtering prevails in almost all practical realizations.

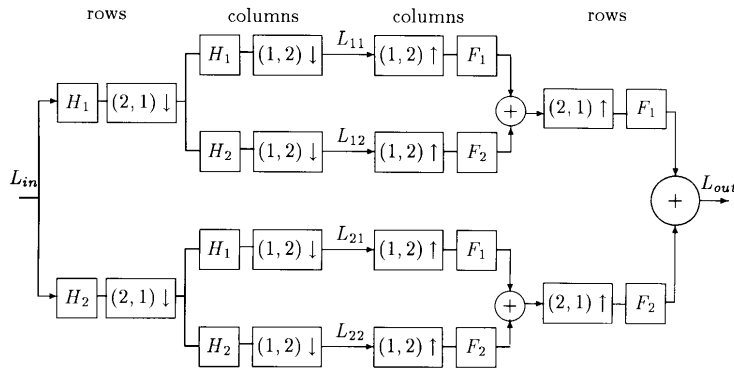


Fig. 2. Separable one-dimensional system for subband analysis and synthesis

One-dimensional filters used to decompose into subbands and reconstruct the image must satisfy the following conditions [10].

$$h_2(n) = (-1)^n h_1(n) \quad (1)$$

$$|H_1(\omega)|^2 + |H_2(\omega)|^2 = 1 \quad (2)$$

$$F_1 = 2H_1, \quad F_2 = -2H_2 \quad (3)$$

and also

$$h_1(n) = h_1(N - 1 - n) \quad (4)$$

which guarantees the linear phase.

In the process of decomposition, the image was decomposed rowwise first, and columnwise afterwards, giving four subbands. Then, the lowest subband was two times recursively decomposed, rowwise and columnwise, giving additional seven subbands.

Quadrature mirror filters (QMF) are often used to decompose image into subbands [3, 9, 10]. In our coding simulations, 16-point one-dimensional QM filter designated as 16A in [3] was used. It has transition bandwidth of $0.14rad$ and an overall passband ripple of 0.008 dB. The stopband rejection

varies from 60 to 75 dB. Although it is well known that better results could be obtained with longer filters (32 or 64-point), our objective was to obtain good results with shorter filter.

3. Application of generalized Max-Lloyd algorithm (LBG algorithm) for vector quantization of subbands

In this work vector quantization was used because it gives better results in bit rate reduction than scalar quantization [7]. For each subband, corresponding to specific orientation of image, the separate codebook was constructed, in order to minimize the distortion resulting from vector quantization. Only the lowest subband, in which most of the energy is concentrated (where most of the information is contained), is scalar quantized for the sake of simplicity [8].

Bit allocation among the subbands is shown in Fig. 3.

Subband b11 is scalar quantized with 256 levels. Subbands b12 and b21 are vector quantized using blocks 2×2 , with codebook length $L=256$. Other subbands are vector quantized using blocks 4×4 . Subband b22 has codebook of length $L=256$. Subbands a12 and a21 have codebooks of lengths $L=64$, and subbands a22, s12 and s21 have codebook of lengths $L=16$. The codebooks are optimized using training set of many different images. Since the test image is not contained in the training set, the code tables do not increase the entropy of the coded test image.

The choice of initial guess is very important for good codebook optimization since the LBG algorithm converges to a local minimum only. In our experiments, a part of one of the images comprising training set is used as initial guess for codebook. It is well known, That for good initial guess, only parts of the image far from the border should be used.

As is usual practice in many experiments, the process of encoding is not actually conducted. Simulation results show only the entropy reduction achieved with bit allocation between the subbands.

The reconstruction of "Lena" 512×512 coded image is shown in Fig. 4. In this case, the achieved peak signal to noise ratio was PSNR= 29 dB, and entropy was $R=0.336$ bits per pixel (bpp). The image with lower resolution 256×256 was reconstructed with PSNR=29 dB and $R=0.852$ bpp.

These results correspond to first order entropy. Further improvements are to be expected when the predictive coding is used (applied to scalar and/or vector quantization), which was not the case in our implementation of subband coding.

b11 SQ 8 b/p L=256	b12 VQ 2 b/p 2 x 2 L=256	a12 VQ 0.375 b/p 4 x 4 L=64	s12 VQ 0.25 b/p 4 x 4 L=16
b21 VQ 2 b/p 2 x 2 L=256	b22 VQ 0.5 b/p 4 x 4 L=256		
a21 VQ 0.375 b/p 4 x 4 L=64		a22 VQ 0.25 b/p 4 x 4 L=16	
s21 VQ 0.25 b/p 4 x 4 L=16			s22 0 b/p

Fig. 3. Bit allocation among subbands: SQ-scalar quantization, VQ-vector quantization

4. Comparison with other results

It is experimentally verified that better results can be achieved with the image resolution of 512×512 than with the image resolution 256×256 . Namely, small bit rate for high subbands results in no visible errors, only the sharpness is deteriorated. The loss of sharpness is less visible on images with higher resolution, especially when reconstructed image is printed in small format. Because of that, it is a common practice in literature to publish subjectively very good reconstructed images with PSNR less than 30 dB.

Another explanation is connected with the fact that for the certain subjective quality of reconstruction the certain quantity of information is needed. Since higher resolution image has more pixels, less bits per pixel are needed, for the same quantity of information to convey.

When the codebook is adaptively transmitted, the overhead is relatively smaller for images with higher resolution, because the dimensions of codebook are only dependent to the number of codewords and independent of image dimension.

It is interesting to compare our results with other results recently published in literature for the same test image "Lena". For example, some results for the resolution 512×512 are:

R=0.3 bpp, PSNR=33.45 dB, [6]

R=0.373 bpp, PSNR=32.21 dB, [5]

R=0.37 bpp, PSNR=30.85 dB, [1]

and for the resolution of 256×256 :

R=0.78 bpp, PSNR=32.10 dB, [1]



Fig. 4. The reconstructed Lena 512×512 image, $R=0.336\text{bpp}$, $\text{PSNR}=29\text{dB}$.

In all these examples the visual criterions are satisfied. It is possible to get numerically better results, for example: $R=0.21$ bpp, $PSNR=29.11$ dB, [1]. However, in that case, the reconstructed image has large white areas on parts where distortions are usually present, probably masking them.

5. Conclusion

The image decomposition into 10 subbands is realized, using QM filters. The subbands were quantized in following way: lowest subband is scalar quantized with 256 levels, and other subbands are vector quantized. For each subband, which correspond to the some specific orientation of the image, the separate code table is constructed, These code tables are optimized training set of many different images. The test image is not contained in the training set.

Very good subjective quality of the reconstructed 512×512 image was achieved, at the first order entropy of about 0.33 bpp and PSNR of 29 dB.

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