FITTING QUANTIZATION SCHEME TO MULTIRESOLUTION DETAIL PRESERVING COMPRESSION ALGORITHM

Artur Przelaskowski

Institute of Radioelectronics
Warsaw University of Technology
ul. Nowowiejska 15/19, 00-665 Warszawa
Poland

ABSTRACT

Adaptive space-frequency quantization scheme in scalar fashion applied to wavelet-based compression is presented. Because of strong demands due to detail preserving in lossy image archiving and transmission, as it is for example in medical applications, different modifications of uniform threshold quantization are considered. The main features of elaborated procedure are as follows: fitting threshold value to local data characteristics in backward way and quantization step size estimation for each subband as forward and backward framework in optimization procedure. Many tests conducted in real wavelet compression scheme confirm significant efficiency of presented quantization procedures. Achieved total compression effectiveness is promising in spite of simple coding algorithm.

2. INTRODUCTION

Key problem in wavelet image coding is to take advantage of the non-stationary nature of image subbands. Previous attempts include spatially adapting subband filters, adaptive schemes of space-frequency quantizers or context-based coding which exploit the dependences in hierarchical structure of data in wavelet domain. We concentrate on the second group of researches: adaptive quantization for efficient wavelet-based image coders but the quantizer should be constructed in jointly optimal manner. Concerning predictable medical applications is the reason of this because quantization is responsible for suitable preserving the diagnostic accuracy of compressed images.

Many bit allocation techniques applied in quantization scheme are based on data distribution assumptions, quantizer distortion function etc. All statistical assumptions built on global data characteristics do not cover exactly local data behavior and important details of original image, e.g. various texture of small areas may be lost.

We consider scalar quantization, which is applied in efficient wavelet coders [1,3,4,7] very often. Although pyramid vector quantization used in [13] gives very good results in some cases. Intelligent solutions of adaptive quantization seem to be important way to increase compression efficiency of wavelet-based methods. Optimal forward, backward and forward-backward schemes are searched on a base of different assumptions and necessary practical simplifications. The basic problem in forward adaptive framework deals with optimal tradeoff between accuracy of high-band wavelet coefficients' distribution modeling and side-information penalty associated with established freedom. For example a settlement between classification gain of two algorithms, which allow unequal number of blocks in each class, and the amount of side information is explored in [2]. In backward adaptive quantization methods adaptation can be done at pixel level since there is no side information [10,11]. But the source modeling in many cases (significant data variability) is not accurate enough because context model has to be causal. Though efficient classification could be performed also in backward adaptation framework [10]. The most promising solutions include both this concepts as forward-backward scheme [9,10]. For instance this idea could be realized as to switch between backward and forward adaptation when a cue derived from causal data signaling unreliability in backward adaptation [9]. Thus some side information must be added to output data stream.

Considerations on entropy constrained scalar quantization prove that uniform quantizers are optimal for high bit rate compression [12]. But established the high resolution quantization hypothesis does not hold in case of low bit rate compression because the quantization bins are too large. Also encoding of the zero quantized coefficients by applying very useful zerotree structure with separated significant data and map coding does not fit assumed simple bit allocation model. In this case uniform threshold quantization (UTQ) has been proved to perform very close to the optimal entropy constrained quantizers for a wide class of memoryless sources [14]. To UTQ belong certain quantizers, which have infinite number of levels and equal step widths. Modifications of UTQ are used in the most efficient compression algorithms [8,9,10].

Exploiting space-frequency wavelet domain characteristic is, in our opinion, a way to find the best solutions. The main idea of this paper is to construct space-frequency quantization by connection of the context-based coefficient importance estimation and thresholding (spatial aspect) and quantization bin modification for each subband as function of the frequency variance. Shortly it is entire context-based thresholding (fitted to each coefficient) + subband fitted uniform quantization (CTSUQ). We tested different quantization schemes. The results of the efficiency comparisons and a description of optimized quantization scheme are presented.

2. ADAPTIVE QUANTIZATION SCHEME

2.1 Compression scheme

We applied typical hierarchical dyadic decomposition scheme with two filter banks: 28/18 taps efficient biorthogonal filter bank [7] and modified biorthogonal coiflets [6]. Coding algorithm is based on zerotree structure and 1[st] order arithmetic coding of significant coefficients' magnitudes and separated sign information [5]. For quantization scheme evaluation 3-level (for 256×256 images) and 4-level (for 512×512 images) decomposition was done, and coiflet filters was applied. In final efficiency evaluation tests optimal number of levels and filter banks were used.

2.2 Optimization of uniform threshold quantization

Optimal for low bit rates entropy constrained scalar quantizer is nearly uniform but not uniform. Non-zero quantization bins have the same size Δ but the zero bin $[-\tau, \tau]$ is larger than $[-\Delta/2, \Delta/2]$. The zero bin ratio $\eta = \frac{\tau}{\Delta}$ is a parameter that must be adjusted to optimize compression algorithm in R-D sense [12]. Larger zero bin called dead-zone reduces those wavelet coefficients which are essentially related to noise. Both experimental [8] and theoretical [12], under certain statistical assumptions, ways of optimal η value estimation were successfully applied. We experimentally estimated optimum η value: 0.8 for Lenna and Barbara test image and 0.84 for Goldhill image. It is very close to the results presented in [8] and [12]. To improve UTQ scheme we investigated the following procedures:

A. The UTQ with dead-zone modification. Optimal zero bin ratio was used.

B. Instead of constant η ratio adaptive zero bin modification was introduced. For each coefficient causal 10-order context was used (fig. 1b) to fit zero bin size to local data characteristic - in context of significant neighbors value of η was increased.

Also another quantization scheme is proposed. The main idea is to increase dead-zone without any modification of scalar uniform quantization. Thus this algorithm can be considered as entire data selection with threshold value exceeding $\Delta/2$ and quantization of remaining coefficients with constant bin size Δ (threshold data selection and uniform quantization - TSUQ). In this case we tested three procedures:

C. The TSUQ. An optimal threshold value, constant for all coefficients was applied.

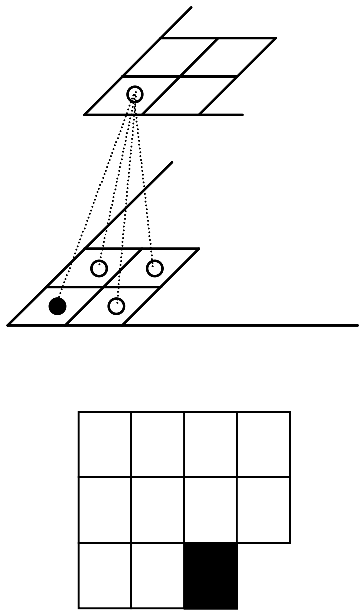
D. The UTQ with dead-zone modification and adaptive threshold data selection. Entirely thresholding in coding process is done. The 3-order context (fig. 1a), definite by parent-children relations in hierarchical decomposition tree, for threshold estimation at each point is used.

E. The adaptive TSUQ. Adaptive modification of threshold value at each point with applying the noncausal 3-order context like in D procedure is done.

On the base of our considerations we propose the algorithm which is modification of E procedure. Bin size Δ is evaluated for each subband on the base of simple statistical model as forward adaptive framework, and modified at each point in backward way. To evaluate the efficiency of described procedures a comparison with UCT was done.

2.3 Uniform quantization with threshold selection (CTSUQ algorithm)

Space-frequency quantization scheme is realised is two steps. Generally we use scalar uniform quantization with step size conditioned by desirable compression ratio and image quality factor. A set of wavelet coefficients is entirely reduced by threshold selection. It is because of the following reasons: a) stronger reduction of unimportant data to improve the quality of compressed images, b) increasing compression efficiency by eliminating single near-zero data (especially effective in zerotree-based coding), c) structure shape and contours enhancement by weaker reduction of grouped significant data and increasing the gradient of edges. Many models of this threshold selection were tested. The best results were achieved by implementing 3-order context square estimate of the data importance. This context corresponds to hierarchical structure of decomposition tree and includes three neighbour points, which possess the same parent node. A square function of importance value for each coefficient modifies initial threshold value of $w/2$ up to 60%. In addition insignificance of a parent node in decomposition tree alters the threshold value up to $\pm 15\%$.



a)

b)

Fig.1. Context for adaptive estimation of threshold value a) and quantization step size b).

Because significant differences in data variability of successive subbands small correction of step size for each subband according to entire variance estimation is realised. Additionally causal context is used for bin modification at each point. The quantization procedure starts with step size value w and this step size is modified up to $\pm 10\%$.

Quantization algorithm

1. Entire helpful data structure creation

a) Creation of the predictive coefficient significance map P. Let's assume that the uniform scalar quantization step size is w and thus initial threshold value is equal to $w/2$. The significance estimation of each wavelet coefficient c_i is simply done as follows:

$$\begin{aligned} &if \quad |c|_i < w/2 \quad then \quad p_i = 0, \\ &elseif \quad |c|_i \le w \quad then \quad p_i = 1, \\ &else \qquad\qquad p_i = 2, \end{aligned}$$

where $i = 1,2,\ldots,m \cdot n$, m,n -horizontal and vertical image size, $p_i \in P$.

b) The variance estimation for the data from each subband. Real wavelet coefficients' distribution is considered. A set of variance data is normalised to 8bit values and must be sent to a decoder.

2. Adaptive threshold value evaluation

The coefficient importance is estimated on the base of P map as a function of significance of three surrounding data. The data context χ_i, shown on fig. 1 a), is formed for each coefficient. The significance of the points which were previously quantized are modified by using the actual threshold values for these points, instead of $w/2$ (causal modification). Factor of spatial coefficient importance is described as:

$$Stm_i = 0.3 \cdot \frac{\left(\sum_{j=1}^{3} p_{i,j} - 6\right)^2}{36}, \qquad p_{i,j} \in \chi_i .$$

The significance of parent node is included as:

$$Ftm_i = 0.15 \cdot (1 - p_{par(i)})$$

Finally adaptive threshold value is counted for each coefficient as follows:

$$Ath_i = w \cdot (0.5 + Stm_i + Ftm_i),$$

where $i = 1,2,\ldots,m \cdot n$.

3. Adaptive quantization bin size evaluation

Quantization step size for each coefficient is described by equation of two factors: established for each subband ξ_l as $Qsub_l$ and estimated for each coefficient c_i from causal prediction $Qcoeff_i$ factor, assumed in the following way:

$$Qsub_l = w(1 + 0.1 \cdot (1 - \mathrm{var}_l / 255)), \qquad l = 1,\ldots,L,$$

where var_l - variance estimation of ξ_l subband data, L - number of subbands, and

$$Qcoeff_i = 0.1 \cdot \frac{\left|\sum_{j=1}^{10} s_{i,j} - 10\right|^3}{1000},$$

where $s_{i,j}$ belongs to 10-order causal context (fig. 1 b) and is counted as:

$$\begin{aligned} &if \quad c_{i,j} \ne 0 \quad then \quad s_{i,j} = 1, \\ &else \qquad\qquad s_{i,j} = 0 . \end{aligned}$$

Thus $Qs_i = Qsub_l \cdot (1 - Qcoeff_i)$, for each $c_i \in \xi_l$.

4. Threshold data selection and quantization

Each coefficient value is firstly compared to entire threshold value and in case of significant magnitude is quantized with Qs_i bin. In data selection for data from LL (lowest frequency subband) a dead-zone is equal to $Qs_i/2$ but for the next subbands the dead-zone is increased to Ath_i value. Threshold selection and quantization for each coefficient c_i is as follows:

$$\begin{aligned} &if \quad c_i \in LL \quad then \quad c_i = c_i / Qs_i \\ &elseif \quad |c_i| < \mathrm{A}th_i \quad then \quad c_i = 0, \\ &else \qquad c_i = c_i / Qs_i \end{aligned}$$

The constant coefficients used in these equations were evaluated experimentally by optimisation of compression efficiency for wide class of tested images.

3. TESTS AND RESULTS

3.1 Performed tests

We used medical test images ($256 \times 256 \times 8$bits): magnetic resonance (MR) and ultrasonic (US), and three other test images: Lenna, Barbara and Goldhill ($512 \times 512 \times 8$bits). For quantization scheme assessment and comparison tests, we realized procedures A, B, C, D, E in the same compression scheme. To evaluate the efficiency of wavelet-based algorithm with CTSUQ a comparison with the most efficient compression techniques like SPIHT [1], SFQ [4], PACC [8], C/B [7], PC-AUTQ [10] and EQ [9] was performed.

3.2 Results

The results are presented on fig. 2 and fig. 3 and in tables: 1 and 2. Presented CTSUQ quantization scheme increases compression efficiency of wavelet-based algorithm over 15% of bit rate in comparison to UCT, and close to 5% in relation to UTQ with dead-zone optimization. Uniform quantization with threshold data selection is more efficient than UCT up to 0.07dB of PSNR. Adaptive threshold selection allows significantly increase effectiveness of TSUQ (up to 0.14dB). Step width modification in forward and backward framework is very efficient in some cases (0.12 dB for Barbara image).

In comparison to SPIHT, improving compression efficiency is: up to 0.7dB of US images and up to 0.5dB for MR images. For other test images effectiveness is even up to 0.6 dB. For medical test images our method is comparable to PACC (± 0.3dB) and generally better than C/B (even up to 0.7 dB). For non-medical test images presented algorithm achieved comparable results to the best reported in image coding literature.

4. CONCLUSIONS

Described research is a trial of optimization of the best known quantization schemes in wavelet-based compression. Uniform quantization with threshold data selection is more effective then UCT with optimized dead-zone. Additional non-zero bin forward and backward modification increases quantization efficiency. Thus compression effectiveness of the whole algorithm, even with simple coding scheme, could be comparable to the best techniques.

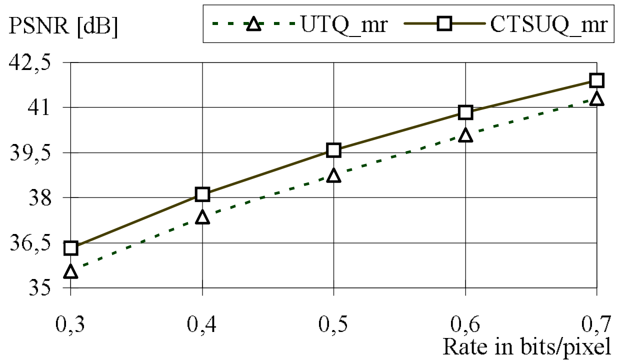


Fig.2. The benefit of applying CTSUQ scheme in wavelet compression algorithm over UTQ; MR test image is used.

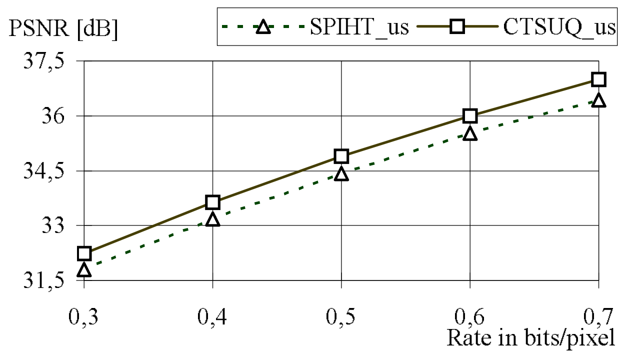


Fig.3. An evaluation of the compression efficiency of two wavelet-based techniques is presented. SPIHT and described method with CTSUQ quantization scheme are compared; US test image is compressed.

Table 1. Comparison of different scalar quantization procedures in wavelet-based compression scheme. PSNR values for 0.25 bpp at each case are presented.

Quant. procedure	Lenna	Barbara	Goldhill
UCT	33.90	27.80	30.16
A	34.21	28.16	30.55
B	34.24	28.22	30.59
C	34.23	28.23	30.59
D	34.31	28.28	30.67
E	34.37	28.27	30.72
CTSUQ	34.40	28.39	30.74

Table 2. The compression efficiency evaluation. Several wavelet-based techniques with different quantization procedures are used. PSNR values for 0.25 bpp at each case are presented.

Comp. technique	Lenna	Barbara	Goldhill
SPIHT	34.11	27.79	30.70
SFQ	34.33	28.29	30.71
C/B	34.57	28.75	30.80
PACC	34.53	28.65	30.84
PC-AUTQ	34.46	-	30.78
EQ	34.57	-	30.76
With CTSUQ	34.40	28.67	30.75

The concept of context-based adaptive threshold and modified quantization step size is effective in stronger reduction of noise but in some cases it occurs too coarse at lower bit rate range. Very small details of the image structures could be putted out of shape. That is the reason why compression scheme in medical applications should additionally include an information about diagnostically important areas as a priori knowledge. CTSUQ procedure could be easy modified and customer or R-D optimization could increase its efficiency.

5. REFERENCES

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