

# IMPROVING SPIHT-BASED COMPRESSION OF VOLUMETRIC MEDICAL DATA

A. Signoroni, M. Arrigoni, F. Lazzaroni, R. Leonardi

Signals and Communications Lab. - DEA - University of Brescia, Italy  
via Branze, 38 - I25123 Brescia, Italy Tel.+39030 3715434 Fax.+39030 380014  
e-mail {signoron,leon}@ing.unibs.it

## ABSTRACT

Volumetric medical data (CT, MR) are useful tools for diagnostic investigation, however their usage may be made difficult because of the amount of data to store or because of the duration of communication over a limited capacity channel. In order to code such information sources, we present a progressive three-dimensional image compression algorithm based on zerotree wavelet coder with arithmetic coding. We make use of a 3D separable biorthogonal wavelet transform and we extend the zerotree SPIHT algorithm to three dimensions. Moreover we propose some improvements to the SPIHT encoder in order to obtain a better rate-distortion performance without increasing the computational complexity. Finally we propose an efficient context-based adaptive arithmetic coding which eliminates high order redundancy. The results obtained on progressive coding of a test CT volume are better than those presented in recent similar works both for the mean PSNR on the whole volume and for the PSNR homogeneity between various slices.

## 1. INTRODUCTION

Today the need to store and communicate large amounts of biomedical image data requires the study of new compression techniques. There exists a rich literature and standardization work (e.g. the upcoming JPEG2000) regarding two-dimensional image coding. Diagnostic imaging techniques, for example computed tomography (CT) or magnetic

resonance (MR), produce a stack of 2D slices making up a 3D volume. Obviously compression of such volume can be accomplished separately for each slice with a traditional 2D image coder. However this does not exploit the strong correlation that may exist between adjacent slices. Such correlation is influenced by the selected resolution along the scanning axis [1],[2]. If the distance between slices in the  $z$  direction is of the same order of magnitude with respect to the  $xy$  resolution, i.e. the voxel anisotropy is low, 3D coding is performing much better than repeated 2D one (or with respect to video coding, due to the lack of classical movement in a 3D scansion) [3],[4],[1] and [2]. The computational coding cost is a critical factor especially for multidimensional data. Nowadays, among the best 2D compression schemes, wavelet based zerotree coding offers high rate-distortion performance with low algorithmic complexities. Moreover zerotree schemes may produce progressive bit-stream and allow an easy extension to Region of Interest coding; these aspects are essential for biomedical applications. In this work we develop a 3D extension of this type of coders. We use a 3D separable wavelet transform, which makes use of the 9/7 spline filters of [5] and the more recent 10/18 tap filters proposed in [6]. These filters have demonstrated very good performance according to objective as well as perceptual criterion for natural images. For the quantization strategy we use the SPIHT algorithm [7] in order to obtain a bit-plane progressive coding. Beyond extending the SPIHT methodology to 3D, we have modified it slightly introducing an improvement in its rate-distortion performance

through the elimination of redundant bits and more advantageous coefficient reconstruction procedure. The output of the SPIHT algorithm is coded [8] in order to eliminate the remaining statistical redundancy. For this purpose we develop a context modeling scheme for 3D SPIHT, based on algorithmic features of the SPIHT and the statistic correlation between various coefficients of the wavelet transform. Finally we test our coding scheme and compare the results to those obtained on a standard volume by two recent similar works [3],[4].

## 2. 3D IMPROVED SPIHT

### 2.1. 2D SPIHT references

We first refer to the 2D SPIHT approach as presented in [7]. SPIHT is a progressive algorithm composed of two iterative steps: a significance map coding and a refinement pass. The first step identifies significant coefficients (i.e. larger than a given threshold which is a power of two) and codes their position. The second step refines the significantly-marked coefficients to reduce the uncertainty interval of these coefficient values. For coding the significance map efficiently, the wavelet coefficients are reorganized in a collection of spatial orientation trees. In fact, in the case of natural data, we can expect a statistical drop of the wavelet coefficients amplitude from roots towards leaves (from low to high resolution). The following sets are used to locate the significant coefficients:

- $\mathcal{D}(i, j)$ : set of all descendants of node  $(i, j)$ ;
- $\mathcal{O}(i, j)$ : set of all offspring of node  $(i, j)$ ;
- $\mathcal{L}(i, j)$ :  $\mathcal{D}(i, j) - \mathcal{O}(i, j)$ .

### 2.2. 3D extension of SPIHT

The extension of the SPIHT algorithm to three dimensions is very easy. In fact it is sufficient to modify the collection of spatial orientation trees by considering also the third dimension. In this way the nodes now have eight sons instead of four. Moreover the wavelet subbands are numbered in such a way to favor, for a same decomposition level, those ones highpass-filtered in the  $z$  direction, because we expect to have higher coefficients in these subbands a cause of the voxel anisotropy.

### 2.3. Optimization of SPIHT algorithm

Beyond extending the SPIHT methodology to three dimensions, we make two changes in the basic algorithm obtaining an improvement in its rate-distortion performance without increasing its computational complexity. First we improve the coding of the significance map by removing some redundant bits. In fact, with reference to the algorithm exposed in [7], there are three situations where the following bit in the encoded stream is certainly equal to one (i.e. the set is significant):

- when the set  $\mathcal{D}$  is significant and all the sons are insignificant then the set  $\mathcal{L}$  is significant;
- when  $\mathcal{D}$  is significant,  $\mathcal{L}$  is empty (we are at the leaves of tree) and the first three (seven in 3D) sons are insignificant then the last son is significant;
- finally when  $\mathcal{L}$  is significant and its first three (seven in 3D) subsets  $\mathcal{D}$  are insignificant then the last set  $\mathcal{D}$  is certainly significant.

Removing these redundant bits from the encoding of the significance map we obviously obtain a better compression ratio.

The second improvement concerns the coefficient reconstruction procedure of the decoder. For each position in the bit stream the reconstructed value of each coefficient is the middle of its uncertainty interval. In the original SPIHT algorithm this value is rounded-up to the nearest integer. But considering the subband coefficient statistics we can reasonably assume the histograms to be mono-modal with a peak in zero and a monotonically decreasing behavior towards higher value. Thus the pdf of the quantization error in each bit-plane interval is slanted towards negative error values. For this reason it is more convenient to round to lower integer. In this way the original bit stream remains the same but the mean square error of the reconstructed image is reduced. Thanks to these two changes we obtain an increment of the PSNR of about 0.1-0.3 dB both for 2D images and for medical CT or MR volumes at rate values from 0.1 to 1.0 bit per pixel; as an example we show in Fig.1 the PSNR increment measured by coding the test volume CT\_SKULL (256x256x128 voxels).

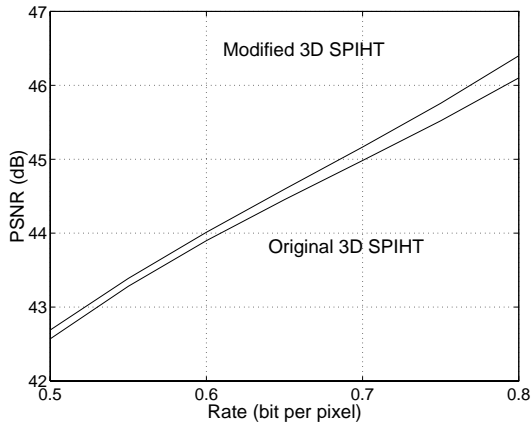


Figure 1: Comparative evaluation of original and improved 3D-SPIHT.

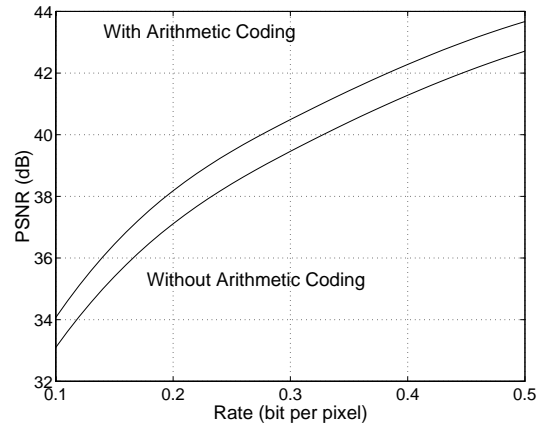


Figure 2: Performance improvement by the use of context based arithmetic coding.

### 3. CONTEXT MODELING IN ARITHMETIC CODING

To increase the coding efficiency the SPIHT bit stream is entropy coded using a context-based adaptive arithmetic coder [8]. For identifying the most useful contexts we analyze here the SPIHT algorithm as a binary memory symbol source. First we can identify three main contexts in the structure of the SPIHT algorithm: sign bits, refinement bits and significance map coding bits. The last context can be subdivided into four sub-contexts: single coefficients, set  $\mathcal{D}$ , set  $\mathcal{L}$  and sons. We have thus six different contexts. At this point we consider some relationships between the wavelet coefficients in the collection of spatial orientation trees. For this reason we identify sub-contexts dependent on the significance value of the father or of the brothers of the node (or set) we are analyzing. This leads to a modeling of the SPIHT source with 26 different contexts.

It is important to note that we entropy code also the refinement bits (contrary to the original SPIHT approach) because, as already seen, the subband coefficient histograms of each bit-plane interval is unbalanced towards lower values and so it is more probable that a coefficient lies in the inferior half-interval rather than in the superior one. Arithmetic coding permits to obtain an increment of the PSNR of 0.5-1.0 dB on three-dimensional data at a rate

ranging from 0.1 to 1.0 bpp, as shown in Fig.2.

### 4. EXPERIMENTAL RESULTS

We test our compression scheme using the same volume CT\_SKULL (256x256x128 voxels) used in [3],[4]. In Fig.3 we show the PSNR calculated on each slice in  $z$  direction for two rate of compression, 0.5 and 0.1 bpp. In this case we used the 9/7 wavelet filters on  $xy$  and the 10/18 ones along the  $z$  direction. The obtained results are better, both for the mean PSNR on the whole volume and for the homogeneity of the PSNR between successive slices as shown in Tab.1 for the 128-slice coding unit at rate of 0.1 and 0.5 bpp. The three methods are compared in whole volume PSNR, worst slice PSNR and PSNR-oscillation range (a measure of the PSNR differences between consecutive or near slices).

The increment in the mean PSNR is obtained thanks to the improvements to the SPIHT algorithm and to the context modeling used in the arithmetic coder. It also benefits from the use of a different wavelet transform. Moreover, the achieved reduction of the oscillation between near slices depends primarily on the selected wavelet. Integer wavelet transforms are used in [3] and [4] in order to guarantee the possibility of lossless compression of the biomedical data, but in lossy condition they work worse. Besides, we argue that

bpp	3DEZW [3]	3DSPIHT [4]	I3DSPIHT
0.1	$\simeq 32.5$	33.99	34.07
	29.8	29.2	30.98
	$\simeq 2.5$	$\simeq 6.0$	$\simeq 2.0$
0.5	$\simeq 42$	42.89	43.67
	39.5	37.5	41.64
	$\simeq 2.5$	$\simeq 4.0$	$\simeq 2.0$

Table 1: Mean PSNR(dB), worst slice PSNR and oscillation range, on 128 slice of the CT\_SKULL volume [3],[4] coded at 0.1 and 0.5 bpp.

SPIHT coding becomes inefficient if pushed to lossless compression, that biomedical data are noisy and so perfect lossless compression is not mandatory as it may seems, and that uncontrolled oscillations of PSNR values between consecutive slice may lead to objectionable artefacts when compression is lossy [2].

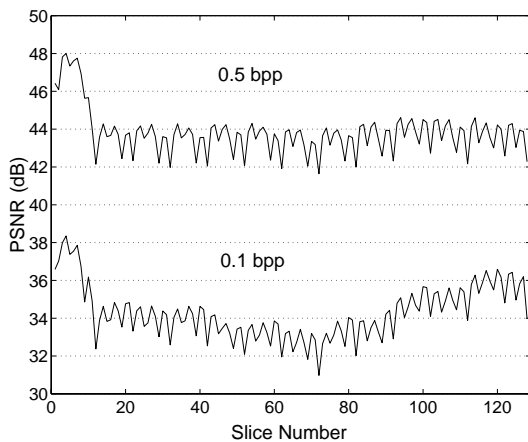


Figure 3: Lossy coding of CT\_SKULL: PSNR on 2D slices for 0.5 and 0.1 bpp.

## 5. CONCLUSIONS

In this paper we proposed an extension of SPIHT based techniques to the 3D case, and suggested how to improve the performance of the SPIHT algorithm without adding any computational cost. We also introduced a set of 3D contexts in order to

obtain a highly performing arithmetic coder. We showed the effectiveness of our approach by applying it to a biomedical test volume and comparing it with respect to others similar works. Based on the obtained experimental results, we suggest not to use integer wavelet filters when this makes worse the objective quality or leads to unpredictable oscillations of the inter-slice PSNR. In conclusion, if lossy compression of biomedical data were acceptable, as it is reasonable, in some clinical contexts (e.g. teleradiology, long term storage archives) the proposed 3D data compression technique could be useful to code not too anisotropic volumes [9].

## 6. REFERENCES

- [1] J. Wang, H.K. Huang. "Medical Image Compression by Using Three-Dimensional Wavelet Transformation". *IEEE Trans. Medical Imag.*, 15(4), 547-554, Aug. 1996.
- [2] A. Signoroni, R. Leonardi. "Diagnostic Compression of Biomedical Volumes". in *EUSIPCO 2000*, 533-536, Sep.2000.
- [3] A. Bilgin, G. Zweig, M.W. Marcellin. "Three-dimensional image compression with integer wavelet transforms". *Appl. Opt.*, 39(3), 1799-1814, Apr.2000.
- [4] Z. Xiong, X. Wu, D.Y. Yun, and W.A. Pearlman. "Progressive coding of medical volumetric data using three-dimensional integer wavelet packet transform". in *VCIP'99 SPIE* vol.3653, 327-335, Jan.1999.
- [5] M. Antonini, M. Barlaud, P. Mathieu, I. Daubechies. "Image coding using wavelet transform". *IEEE Trans. Image Proc.*, 1(2), 205-220, Apr.1992.
- [6] M.J. Tsai, J. Villasenor, F. Chen. "Stack-run image coding". *IEEE Trans. Circ. and Sys. for Video Tech.*, 6(5), 519-521, Oct.1996.
- [7] A. Said and W.A. Pearlman. "A New, Fast, and Efficient Image Codec Based on Set Partitioning in Hierarchical Trees". *IEEE Trans. Circ. and Sys. for Video Tech.*, 6(3), 243-250, Jun.1996.
- [8] A. Moffat, R.M. Neal, I.H. Witten. "Arithmetic Coding Revisited". *ACM Trans. on Information Systems*, 16(3), 256-294, July 1998.
- [9] A. Signoroni. "Representation and Compression Methodologies for Biomedical Volumes". PhD thesis, University of Brescia, (*in Italian*), Feb.2001.