LOSSY COMPRESSION OF VOLUMETRIC MEDICAL IMAGES WITH 3D DEAD ZONE LATTICE VECTOR QUANTIZATION

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ABSTRACT

This paper presents a new lossy coding scheme based on 3D Wavelet Transform and Lattice Vector Quantization for volumetric medical images. The main contribution of this work is the design of a new codebook enclosing a multidimensional dead zone during the quantization step which enables to better account correlations between neighbour voxels. Furthermore, we present an efficient rate-distortion model to simplify the bit allocation procedure for our intra-band scheme. Our algorithm has been evaluated on several CT an MR image volumes. At high compression ratios, we show that it can outperform the best existing methods in terms of rate-distortion trade-off. In addition, our method better preserves details and produces thus reconstructed images less blurred than the well-known 3D SPIHT algorithm which stands for a reference.

Index Terms— Lossy Compression, volumetric medical images, 3D wavelet transform, 3D Dead Zone Lattice Vector Quantization.

1. INTRODUCTION

Most of the current medical imaging techniques produce three-dimensional data. Some of them are intrinsically volumetric, like Positron Emission Tomography (PET), Computerized Tomography (CT), Magnetic Resonance (MR), 3D ultrasound, while others describe the temporal evolution of a dynamic phenomenon as a sequence of 2D images (they are more properly labelled as 2D+time). The huge amount of data generated every day in the hospital environment yields compression to be unavoidable for efficient storage and transmission purposes.

Compression schemes can be divided into two groups: lossless compression and lossy compression. Nowadays, compression methods used in medical applications are most of the time lossless methods in order to preserve the data integrity and to facilitate thus a true diagnosis. However, lossless coding does not permit to reach high compression ratios. Thus, most of applications (e-g: telemedicine, fast searching and browsing of medical volumetric data) suffer from this limitation. For this kind of applications, lossy compression seems to be an appropriate alternative. Furthermore, in many applications like for example computer aided detection (CAD) [1], it has been shown that a balance between data compression and data fidelity could be achieved [2].

A volumetric medical image is a three-dimensional (3-D) image data set which can be considered as a sequence of two-dimensional (2-D) images (or slices). A direct way to perform compression on it is to straightforwardly apply a two dimensional compression algorithm to each slice independently. However, the slices are generally highly correlated with one another. Thus, the basic idea of the 3D medical image compression algorithms is to take advantage of the correlation among the data samples in the three dimensional space to improve compression performances. The most approaches combine a three-dimensional space decorrelating transform with the extension of a coding algorithm that has proven to be effective on 2D images [3]. For example, Catin *et* al [4] were the first, to our knowledge, to compress volumetric medical images with Lattice Vector Quantization (LVQ), while many works had been done before on LVQ [5] [6] in the field of 2D real life images.

In this paper, we propose the design of a new entropy-coded LVQ codebook enclosing a multidimensional dead zone to encode the coefficients of a 3D Dyadic Wavelet Transform (3D DWT) which is known to be one of the most efficient decorrelator for 3D medical images [3] [4].

One of the main advantages of the proposed scheme – called 3D Dead Zone Lattice Vector Quantization (3D DZLVQ)- is its ability to remove non significant vectors while quantizing more accurately significant ones, which yields a significant improvement of the overall rate-distortion trade-off. Moreover, we introduce an efficient bit rate allocation procedure based on the approximation of the rate distortion (R-D) functions by an exponential model. Numerical and visual results produced by 3D DZLVQ on MRI and CT images are promising at low rates by comparison with a set of the best 3D coders published in the literature.

2. 3D DEAD ZONE LATTICE VECTOR QUANTIZATION

The whole lossy compression scheme we propose is represented in Figure 1. The coefficients produced by the 3D DWT within each subband are scaled and quantized by the 3D DZLVQ algorithm in an intra-band framework (dependencies between resolutions are not taken into account). The main advantage of LVQ-based methods is their low complexity since there is no need to construct or store the codebook. Quantized vectors Y are finally encoded by using an efficient prefix code which associates to Y a unique pair (e,pos), where $e = \|Y\|_1$ and pos stands for the position of Y on the shell of radius e. For efficiency in terms of bit rate, e is encoded using entropy coding while pos is fixed-length coded [7]. The bit rate related to a subband is then:

$$R = -\sum_{r=0}^{r_T} P(e = r)\{\log_2 P(e = r) - \lceil \log_2 N(r) \rceil\} \text{ bits/vector (1)}$$

where $N(r)$ is the population of the shell of radius r (i.e. the number of codebook vectors whose norm[1] is equal to r), P the discrete law of the radius and r_t the truncation radius of the codebook.
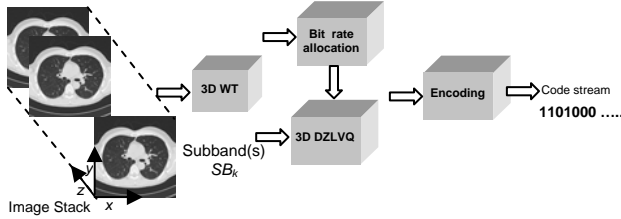

Figure 1: Proposed whole lossy compression scheme.

Here we propose to decrease R at a fixed distortion D (or equivalently to decrease D at a fixed rate R) by designing a multidimensional dead zone of radius R_{DZ} within the codebook. Our scheme allows to threshold non significant source vectors according to a criterion based on their norm, while putting more bits on significant ones. It can efficiently apply to medical images in the 3D wavelet domain which often contain huge non-significant areas (for instance the areas where no anatomy is imaged).

Furthermore, the norm of vectors is a good measure of the local activity in the case of correlated and sparse source samples like wavelet coefficients under the condition of vectors oriented along the direction of the details of the corresponding subband. To discuss this issue, let us make a comparison between the histograms of the norm of three kind of vectors: Figures 2 (A) to (C)

correspond to the $LHL_3{}^2$ subband (vertical details + low pass filtering along z) of liver_t2 image (see Table 1) for three different vector orientations: vertical (8×1×1), horizontal (1×8×1) and cubic (2×2×2) respectively. Distribution (A) is more picked than (B) since an orientation along the direction of wavelet details allows to better capture clusters of significant coefficients and to increase the number of vectors around zero. This point shows that for coding efficiency purposes one should not privilege vectors orthogonal to the direction of the 2D wavelet subband details. Moreover, as we perform a 3D DWT, additional correlation exists along the temporal direction (z) as it is shown in Figure 2(C) with the cubic orientation of vectors. This last one represents actually a good compromise for capturing clusters in the three directions in all the subbands. Logically, the cubic orientation gives the best R-D function of 3D DZLVQ for all the subbands. So, will be used in our work.
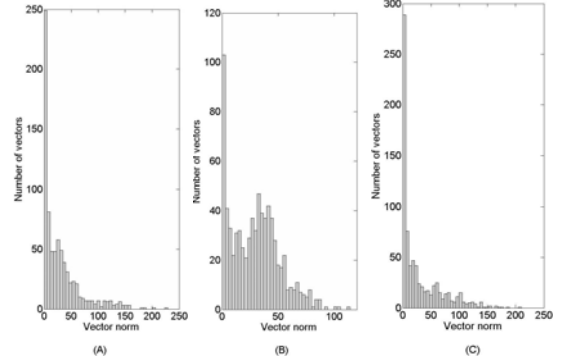

Figure 2: Histograms of the L^1 norm of the LHL3 subband of *Liver t2*: 8 x 1 x 1 vectors (A), 1 x 8 x 1 vectors (B), 2 x 2 x 2 vectors (C).

In the proposed framework, according to the vector dead zone radius R_{DZ}, the quantization process of any source vector X becomes the following (see Figure 3):
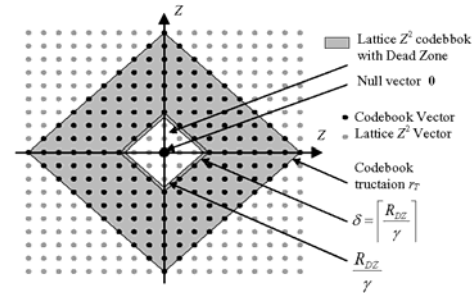

Figure3: 3D DZLVQ codebook for vectors of size

If $\|X\|_1 \leq R_{DZ}$, X is replaced by the null vector **0**.

If $\|X\|_1 > R_{DZ}$, X is scaled by γ (the scaling factor) and quantized by usual fast lattice quantization algorithms [7]. Note that the parameters (γ, R_{DZ}) enable to tune the trade-off between rate and distortion.

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[1] In the whole paper the norm stands for the L^1 norm.

[2] L and H mean low pass and high pass filtering respectively. The filtering direction follows the order *x, y* and *z*. The final number indicates the level decomposition

3. BIT RATE ALLOCATION PROBELM

As, we use an intra-band approach to quantize and to encode the wavelet coefficients, it is necessary to implement a rate allocation algorithm to assign a bit rate to each subband SB_k of the multiresolution decomposition, while minimizing the overall distortion, under the constraint to reach the total bit rate. This is a difficult problem (especially for volumetric images) which can be solved by lagrangian multiplicators based methods at the price of a high computational complexity. A lot of effort has been done for years by many researchers to develop analytical rate-distortion models dedicated to wavelet coefficients to decrease the complexity of the allocation procedure. However, these models are generally built on the i.i.d. hypothesis [6] [8] while block based methods (like LVQ) could take advantage of non i.i.d. properties of real data such as wavelet coefficients. In the 3D DZLVQ case, this drawback can be circumvented. Indeed, as 3D DZLVQ increases the amount of null vectors, it modifies the shape of the R-D function in the low rates range in a way that it can be modeled by a single exponential function $D(R)=Ce^{-aR}$ with C and a the parameters of the model.

These parameters can be computed using a simple linear regression. Let L be the number of R-D points used in the regression and $d_k = D(R_k)$, $k = 1,...,L$ be the distortion value associated to the bit rate R_k of subband SB_k. The parameters of our model are then:

$$C = \exp\left(\frac{L\sum_{k=1}^{L} R_k d_k - \sum_{k=1}^{L} R_k \sum_{k=1}^{L} d_k}{L\sum_{k=1}^{L} R_k^2 - \left(\sum_{k=1}^{L} R_k\right)^2} \right) \qquad (3)$$

$$a = -\frac{1}{L}\left(\sum_{k=1}^{L} d_k - \ln(C)\sum_{k=1}^{L} R_k \right) \qquad (4)$$

Practically, we can show that only three R-D points are necessary to compute C and a. Figure 4 permits to compare the experimental R-D function of LHL$_2$ subband of *Liver_t2* image and the approximation given by our model. As we can see, the proposed model is accurate.
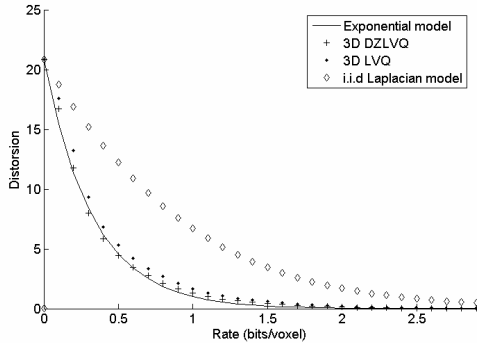

Figure 4: Comparison of R-D functions obtained with LVQ, 3D DZLVQ, i.i.d Laplacian model and proposed exponential model – LHL2 subband of *Liver t2*

Finally, it offers substantial reduction of the computational complexity of rate allocation as it leads to an analytical solution to this problem. The interested reader may consult the reference [9] related to the 2D case for more precision.

4. EXPERIMENTAL RESULTS

In order to give a fair comparison with existing works, we have tested our 3D DZLVQ algorithm for lossy compression on the 8-bit CT and MR volumetric medical image data set used in Bilgin *et al*'s work [3]. Table 1 shows the description of these images. The first slices of each data set are shown in Figure 5.

	History	File name	Voxel size(mm)	Volume size
CT	tripod fracture	Skull	0.7x0.7x2	256x256x128
	scaphoid fracture	Wrist	0.17x0.17x2	256x256x176
	carotid dissection	Carotid	0.25x0.25x1	256x256x64
	Apert's syndrome	Aperts	0.35x0.35x2	256x256x96
MR	Normal	Liver_t1	1.45x1.45x5	256x256x48
	Normal	Liver_t2	1.37x1.37x5	256x256x48
	Left Exopthalmos	Sag_head	0.98x0.98x3	256x256x48
	Heart disease	Pad_chest	0.78x0.78x5	256x256x64

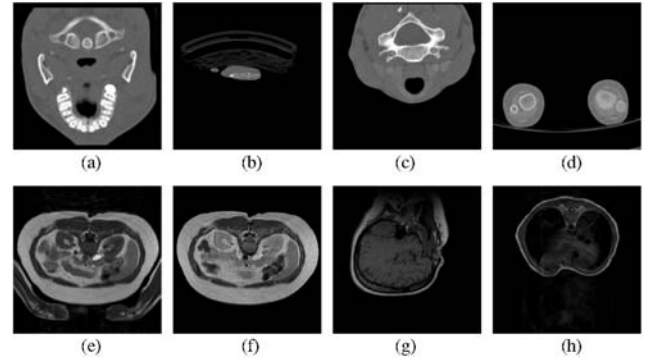Table 1: Description of the data sets in our experiments.

Figure 5: Caption of volumetric medical images : First slice of each data set (a) *Skull* (b) *Wrist* (c) *Carotid* (d) *Aperts* (e) *Liver_t1* (f) *Liver_t2e1* (g) *Sag_head* (h) *Ped_chest*

First, we compare the compression performances of our method with those of both classical 3D LVQ [4] and 3D-SPIHT [10] [11]. All the images have been compressed by the three methods at rates varying from 0.05 to 1 bit/voxel (bpv). We have used the well-known 9.7 floating-point filter [6] with a four-level 3D DWT or a three-level 3D DWT when the resolution was limited along the z axis ($T_Z < 64$). Furthermore, we have designed a pyramidal codebook whose dead zone and scaling factors (within each subband) have been chosen to optimize the overall rate-distortion trade-off.

Table 2 shows that at a low rate (0.1 bpv) 3D DZLVQ outperforms 3D LVQ and 3D SPIHT, in terms of PSNR, except for *Wrist* and *Aperts* images. Note that tests at other low rates (lower than 0.5 bpv for *Skull* and 0.35 bpv for the remaining images) have lead to the same kind of results. 3D SPIHT is better at high rates (in terms of

PSNR) since the efficiency of the vector dead zone naturally decreases at such rates.

	3D DZLVQ	3D SPIHT	3D LVQ
Skull	**34.69 dB**	33.98 dB	33,46 dB
Wrist	43.63 dB	**44.95 dB**	43.29 dB
Carotid	**41.08 dB**	40.51 dB	40.24 dB
Aperts	46.98 dB	**47.41 dB**	46.66 dB
Liver_t1	**38.84 dB**	38.37 dB	38.02 dB
Liver_t2el	**36.61 dB**	36.31 dB	36.12 dB
Sag_Head	**39.03 dB**	38.76 dB	38.55 dB
Pad_chest	**42.98 dB**	42.97 dB	42.18 dB

Table2: Mean PSNR (dB) Comparison between 3D SPIHT, 3D LVQ and 3D DZLVQ at.0.1 bits/voxel (bpv) on the 8 database images detailed in Table

Furthermore, table 3 summarizes some results achieved by other 3D methods on the *Skull* image which is abundantly used in the literature [3], [10]-[12]. 3D EZW [3] is a recent extension of well-known EZW algorithm. 3D ESCOT is a 3D version of EBCOT algorithm using a uses a (2+2, 2) filter with a four-level integer wavelet packet transform and a very sophisticated context-modeling [12]. Table 3 confirms the superiority of the proposed algorithm in terms of PSNR at low rates.

	3D SPIHT	3D DZLVQ	3D EZW	3D ESCOT
0.5 bpv	44.11 dB	**44.14 dB**	39.82 dB	43,82 dB
0.1bpv	33.98 dB	**34.69 dB**	31.68 dB	34,68 dB

Table3: PSNR (dB) Comparison on 128 slice *Skull* between 3D SPIHT, 3D ESCOT, 3D CB-EZW, 3D LVQ and 3D DZLVQ

Finally, Figure 6 provides a reconstructed slice of the *Skull* image, after a compression at 0.1 bpv on the whole image by both 3D DZLVQ and 3D SPIHT. We can see that at this rate, our method seems to better preserve details, producing thus an image less blurred than 3D SPIHT. Note that at high rates, it seems more difficult to note differences between the methods.

5. DISCUSSION

We have presented here a new lossy compression method for volumetric medical images. It is based on a 3D wavelet transform followed by a 3D dead zone lattice vector quantizer. Our scheme exploits intra-band dependencies, contrary to methods like 3D SPIHT which take into account dependencies existing between wavelet coefficients at the different resolution levels of the 3D DWT, using zerotrees. Our scheme requires an efficient bit allocation to assign a bit rate to each subband of the wavelet decomposition, while minimizing the overall distortion. Zerotrees based methods are simpler but sensitive to the propagation of errors through the resolution levels.
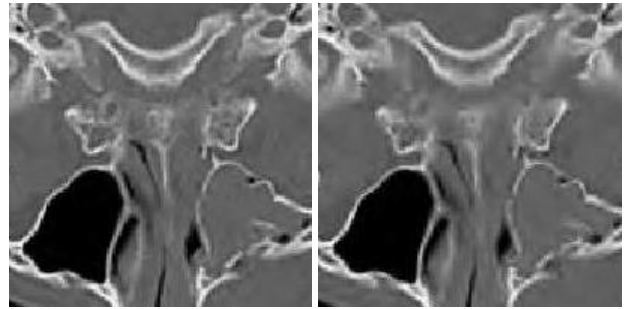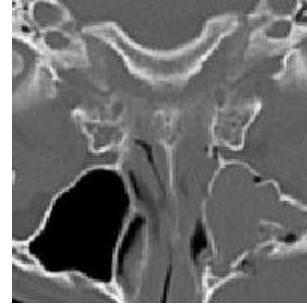

Figure 6: Zoom of decoded slice 60 (*Skull*) when the target decoding bit rate is 0.1 bpv for the whole 128-slice unit. Clock-wise from the top to the bottom left: Original slice, 3D SPIHT, 3D DZLVQ.

The estimation of the computational complexity of the algorithms used in this work is not a trivial task. Indeed, 3D SPIHT accounts the dependencies between the wavelet subbands which are exploited through zerotrees. The computational complexity (in operations/voxel) of such a structure cannot be expressed. On the other hand, contrary to 3D SPIHT, our proposed 3D DZLVQ algorithm is based on an intraband approach and requires consequently a bit allocation procedure which increases the whole complexity, making 3D DZLVQ a slower algorithm than 3D SPIHT. However, thanks to the proposed analytical solution to the bit allocation problem, the reduction of the complexity is significant. For the medical image data set and the range of bit rates used in the paper, we can show experimentally that the whole computational complexity of 3D DZLVQ falls down to about 66 operations/voxel. The use of our method is thus realistic in a medical data compression application. Furthermore, it is highly parallelizable due to the intraband characteristic.

Our method achieves lossy compression competitive with the best results published in the literature in terms of PSNR. Moreover, it produces reconstructed volumetric medical images visually better than 3D SPIHT, which is known as one of the most efficient methods for this kind of images. This seems to be due to the combination of several points. First, the vector orientation along the details within each subband allows to better capture clusters carrying significant information. In addition, the L^1 norm of vectors seems to be an appropriate criterion to discriminate significant information from non significant one. Finally, the proposed pyramidal deadzone allows to threshold non significant vectors increasing thus the

amount of vectors quantized by the null vector, which is advantageously exploited by our entropy coded 3D DZLVQ algorithm. By this way, it is possible to decrease the overall distortion at a constant rate or equivalently to decrease the bit rate at a constant distortion. The improvement of the rate-distortion trade-off can be reached in most of the wavelet subbands, especially in the high and average resolutions of the wavelet decomposition, which yields a better overall visual quality and the preservation of small details.

In order to be fair in the performance evaluation, it is necessary to take into account an important issue. It is well-known that the PSNR is a global criterion which is not sufficient to measure the quality of the reconstructed images, especially in medical applications where the evaluation should be done by experienced radiologists over a large data set. Unfortunately, such studies are very expensive in terms of time and human means. This is the reason why, at our knowledge, none recent works on the actual 3D lossy coders of the literature uses a medical opinion.

Our goal in this paper is mainly to present a new lossy compression algorithm dedicated to the specificities of volumetric medical images. First results reported here are promising as they show gains in terms of PSNR with respect to the best coders published in the literature. Furthermore, the proposed algorithm seems to improve the overall visual quality by producing less blurred reconstructed images at low rates. As mentioned previously, these results should be evaluated by medical experts in terms of visual quality. However, note that first results of another study on compression of 12 bit ENT CTs we drive with two medical experts of the Centre Alexis Vautrin of Nancy - France (centre specialized in cancerology) confirm the superiority of the proposed method over 3D SPIHT for this kind of images. Thus, the next step of our work will include an evaluation of observer performance with medical experts at a larger scale.

6. CONCLUSION

We have presented a new 3D medical image compression method based on a multidimensional dead zone which achieves lossy compression competitive with the best results published in the literature in terms of PSNR. By assigning more bits on significant vectors according to a norm-based criterion, our method allows to better preserve fine structures and produces a better overall quality of the reconstructed images which is of importance in medical applications.

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