LOSSY TO LOSSLESS SPIHT-BASED VOLUMETRIC IMAGE COMPRESSION

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ABSTRACT

A new coding scheme for lossy-to-lossless compression of volumetric data using three-dimensional packet wavelet transform is presented. The need of unitary transform via the integer lifting scheme and the performance comparison of different integer filter kernels is discussed. A state-of-the-art coder, Set Partitioning In Hierarchical Trees (SPIHT), is considered and modified in order to adapt its tree-structure to the 3D packet wavelet structure defined. The algorithm is extensively tested and shows very good performance, both for lossy and lossless coding.

1. INTRODUCTION

Volumetric image compression is highly desirable in the scientific and medical field. Given the nature of the data and all possible applications, a coding scheme should offer various features; progressive data transmission, or scalability, region of interest (ROI) coding capability and random access to the data volume or part of it are just three examples of useful features. Another important requirement is the capability of up-to-lossless coding. In the case of medical imaging, lossless or near-lossless compression is often mandatory, while lossy compression is accepted for fast browsing or representation purpose. In fact, discarding of even small details might result in the loss of important information with severe diagnosis faults. A good compression scheme should then offer a reasonable trade-off between rate-distortion performance and the various features described above.

Several works have addressed the problem of lossy-tolossless coding of volumetric data with integer wavelet transforms. Xiong *et al.* [1] proposed a modified version of 3D SPIHT and 3D ESCOT with the introduction of packet wavelet decomposition and the study of context modeling. Schelkens *et al.* [2] gave an overview of several techniques and proposed a new method based on quad-tree and block-based coding. They also provided a new 3D DCT-based scheme. Integer wavelet transforms for 3D compression are further investigated by Bilgin *et al.* [3], who introduced a scheme based on 3D zero-tree coding and Kim *et al.* [4], who employed a slice-based subdivision of the volumetric image and tested several integer wavelet kernels together with the 3D SPIHT algorithm.

Other works try to optimize the compression through objectbased methods. This is generally done through preliminary segmentation, aimed at extracting useful information and discard of the background. Example of such approaches is the work from Menegaz *et al.* [5]. Visualization-oriented compression is considered in other studies. Bajaj *et al.* [6] adopted a lossy compression scheme combined with a technique to weight voxel values according to their importance for visualization. Finally, fast random access was addressed by Nguyen *et al.* and Ihm *et al.* in [7] and [8] respectively.

This work proposes a new lossy to lossless volumetric coding scheme (3D-SPIHTp hereafter) based on packet integer wavelet transform and SPIHT [9]. In particular, a custom SPIHT coder is implemented in order to comply with the chosen decomposition structure

The paper is structured as follows. In section 2 the background of this research is briefly described. The proposed algorithm is presented in section 3. In section 4 the results are shown for different datasets and modalities. Finally, in section 5 are the conclusions.

2. BACKGROUND

2.1. Lifting integer wavelet transform

Discrete wavelet transform (DWT) is widely used in signal processing. It relies on the property of compacting most of the signal energy in a few relevant coefficients and defining a larger number of "detail" coefficients for better approximation. The lifting scheme was presented by Sweldens [10, 11] to allow for an efficient implementation of the discrete wavelet transform, with perfect reconstruction granted by the structure of the scheme itself. Moreover, an integer transformation can be obtained through the lifting scheme by rounding each filter output to the nearest integer. Such transform conspicuously reduces the number of arithmetic operations compared to the filter-bank implementation and its structure guarantees full reversibility, regardless of the filter used. As a main drawback, it has been observed that integer transforms offer worse energy compaction performance compared to the real case.

For our research, the following filters have been considered and evaluated: I(2,2), I(2,4), I(4,2), I(4,4), I(2+2,2) and S+P with A, B and C parameter sets. In particular, the S+P filter was introduced by Said and Pearlman as an improvement of the S transform [12].

2.2. Packet wavelet transform

Several recursion schemes have been used for data compression. The dyadic decomposition is certainly the most famous; it relies on iterating the transformation stage on the low-passed signal only. Other schemes are generally grouped in the category of *Packet Wavelets*, defined as any one of a collection of orthonormal transforms, each of which can be computed using a simple modification of the pyramid algorithm for the DWT.

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Such scheme has been adopted, among other reasons discussed in the following, in order to avoid potential problems related to the scaling of the integer lifting scheme. While all considered filter pairs meet the perfect reconstruction constraint, they result in non-unitary transforms. For this reason, a non integer scaling factor is generally needed after each filtering operation. In the case of two dimensional signals, such as conventional images, application of the transform produces scaling factors of perfect integer precision. On the other hand, three dimensional signals, such as volumetric data, cannot rely on such property. By using the proper packet decomposition scheme and an even number of decomposition levels, such drawback can be avoided, as described in [1].

2.3. SPIHT

Set Partitioning In Hierarchical Trees was introduced by Said and Pearlman [9] as a novel low-complexity and efficient image coder. It allows for progressive transmission by sorting the transform coefficients in order of significance and exploiting the redundancy in the tree structure of the wavelet transformed image. The algorithm relies on three linked lists, called list of insignificant sets (LIS), list of insignificant pixels (LIP) and list of significant pixels (LSP), which are dynamically modified during execution. The method consists of two main steps called *sorting* and *refinement* pass.

The main advantages of SPIHT are its efficiency, adaptability and precise rate control. In fact, it is possible to stop the coder/decoder at any time, in order to obtain one exact bitrate. Alternatively, running the process until the last bitplane results in lossless coding, provided the wavelet coefficients were not subjected to quantization.

3. PROCESSING STRUCTURE

The codec infrastructure is discussed in the following sections. The general coding scheme is described in section 3.1, while issues related to the decomposition scheme; refinement step and context entropy coding are covered in sections 3.2 to 3.4.

3.1. Coding scheme

The proposed volumetric coder adopts the general scheme for transform-based coders. The input volumetric data can be initially tiled in GOS (Group Of Slices) or blocks, so that each tile is considered independently.

Each tile is further transformed by the 3D integer lifting wavelet transform described in section 2.1 and 2.2. The separable transform is first applied along the z axis (z or interslice dimension) with the packet wavelet decomposition illustrated in section 2.1. The dyadic transform is then applied to each slice (xy or *intra-slice* dimension). Thanks to this scheme, a different number of decomposition levels is applicable to the inter- and intra-slice transform. At the same time, we can choose among the integer filters referred in 2.1 to be applied along z or xy independently. Such feature is useful to choose the best combination of filter type and decomposition levels. In fact, directional anisotropy implies that voxel correlation is generally greater inside each slice than between slices, allowing for better intra-slice redundancy exploitation. For such reason, it is reasonable to adopt integer filters of smaller size and a smaller number of decomposition levels for inter-slice dimension. In

brief, besides offering the integer scaling capability discussed in section 2.2, the packet transform consents to avoid the limitations of dyadic decomposition, which implies symmetry even when such property is not granted.

Each transformed tile is then passed to the 3D-SPIHTp core. This block provides scalable data redundancy exploitation by decomposition of the transformed tile into hierarchical tree. The main part is an extension of the SPIHT algorithm to 3D data that implements the packet decomposition hierarchy. Further context entropy coding can be implemented inside the core itself and is discussed in section 3.4.

The decoding process simply follows the encoding in reverse order; 3d-SPIHTp decoder, inverse integer lifting filters and block composer are provided in order to perform the full decoding stage.

3.2. 3D packet decomposition

In order to exploit the same packet structure of the wavelet transform, the SPIHT coder must be accurately modified and integrated. While intra-slice decomposition follows the conventional dyadic structure, inter-slice samples are not related by a factor 2 scaling. In particular, while the highest level subband, LL_N , has only one correspondent plane in each other subband of same level, LH_N , HL_N and HH_N , each of these can be considered parent of 4 other planes at the corresponding subband at *N*-1 level (Fig. 1).



Fig. 1. Sample decomposition structure for the 3D-SPIHTp codec.

This rule becomes regular after the N-1 level, so that each plane of a certain subband is the parent of 4 other planes at the corresponding subband at the lower decomposition level. This structural choice allows for the exploration of the whole volume with correct hierarchical dependence. In all cases, child planes are retrieved with a scaling factor and a shifting coefficient, instead of a simple scaling of 2 as for dyadic decomposition

In the SPIHT algorithm the structural relation is evidenced by information of the LIP and LSP, with the definition of two types of sets: set with insignificant descendants (A-sets) and set with insignificant descendant of offspring (B-sets). In order to exploit the previously described structure the coder has been modified with the introduction of four new set types. Types X and x designate root sets for subbands inter-slice decomposition at the highest decomposition level, while Z and z represent sets for subbands decomposition along the z axis at lower decomposition levels. With capital or lower-case letter we indicate the corresponding set with insignificant descendants or insignificant descendant of offspring respectively, as for A and B sets.

3.3. Refinement pass

In the wavelet decomposition, each subband coefficient is scaled according to its spatial location to obtain a unitary transform. Given the chosen decomposition structure, multiplicative scaling factors are always powers of 2. Such operation is equivalent to bit-shifting the coefficients.

During the refinement pass, which is performed after all sets and insignificant voxels have been tested for significance in comparison with a certain bit-plane *n*, coefficients belonging to the LSP are refined by outputting their n^{th} bits. Consequently, all coefficients belonging to subbands that have been scaled by a factor of 2 or greater can produce irrelevant output. In lossless compression, for instance, each scaled coefficient produces an irrelevant output bit each time it is compared with a threshold lower than its scaling factor.

In order to solve such problem, a simple conditional scheme can be added to the co-decoder; location of each coefficient together with dataset size, decomposition levels and current bitplane must be considered to decide for that element's further processing.

3.4. Context entropy coding

The 3D-SPIHTp coder is able to exploit spatial and frequency redundancy of the wavelet compressed volume while ordering its hierarchical structure to provide a fully scalable bitrate. However, the output produced by each coding stage still presents a certain level of correlation. In order to increase the performance, additional entropy context coding can be applied. In particular, the output deriving from the processing of A sets during the sorting pass was revised, which constitutes 50% of the coded stream on average. Each time an A set is considered significant, a significance output bit is produced for each of its four offspring. Consecutively, each time one of these is found significant, a corresponding sign bit is produced. This leads to 81 possible symbols of different length.

It has been noted that smaller symbol length does not always correspond to higher probability. In particular, sets with one significant offspring are more probable than sets with no significant offspring, which are coded with fewer bits. At the same time coefficient sign showed a certain correlation depending on the chosen wavelet filter. Finally, it has been noted that almost 60% of occurrences is provided by 10 symbols only.

To increase performance, a simple adaptive Huffman coder has been adopted. As a result, the A-set output decreased by an average factor of 11%, resulting in a final gain of approximately 5%. Such figures can be further increased with the implementation of more sophisticated techniques and the extension of such considerations to other sources of output.

4. EXPERIMENTAL RESULTS

In order to evaluate the performance of our method we consider the same 8bit CT and MR volumetric dataset used in [1] and [3] for easy comparison. The images present different techniques, sizes, and information content. In order to test extensively the features of the proposed technique, the following parameters are considered: decomposition levels (intra- and inter-slice), filter type (intra- and inter-slice) and bitrate

For lossy compression, the peak SNR (PSNR) is used as objective quality metric. In section 4.1 lossless results are discussed, while in section 4.2 lossy compression is considered

4.1. Lossless compression

We test 3D-SPIHTp on the whole CT and MR datasets. All coding results are reported in terms of bits per voxel (bpv) based on real compressed file size.

In tables I and II we compare the different integer wavelet filters referred in section 2.1 for the CT and MR datasets respectively. Filter types refer to the intra-slice transform, while the adopted inter-slice transform is (2,2) for all experiments. In all cases, a single coding unit equal to the full slice number was used to compress the volumes. Best results are shown an bold numbers. It can be noticed that the (2+2,2) filter kernel outperforms all other kernels for all datasets except for MR_liver_r2 , where (4,2) prevails. Although inferior to [13], where a similar asymmetric decomposition tree was adopted with different inter-slice wavelet, results are comparable with those reported in [1] and [3].

Comparison of different coding unit sizes is shown in table III. The CT_wrist dataset has been coded with 5 decomposition levels and (2+2,2) filter intra-slice and variable decomposition levels and (2,2) filter inter-slice. GOS of 16, 32, 64, and 128 slices are reported. It is possible to notice the decreasing trend of the coding rate while GOS size increases. However, for constant GOS size, a higher number of z decomposition levels does not provide better performance. This could be explained by the reduced inter-slice correlation due to the significant difference between transversal and planar resolution (ratio of 0.085).

TABLE I. Comparison of different wavelet transforms on the CT dataset

	Wavelet transform							
Name	(2,2)	(2,4)	(4,2)	(4,4)	(2+2,2)	S+P A	S+P B	S+P C
CT_skull	2.074162	2.084404	2.072756	2.072871	2.067591	2.202656	2.178009	2.165796
CT_wrist	1.382904	1.385376	1.372028	1.372230	1.369475	1.560496	1.585457	1.574711
CT_carotid	1.588280	1.596066	1.581793	1.581924	1.579716	1.647465	1.617043	1.602703
CT_aperts	1.081957	1.087734	1.081394	1.082203	1.078274	1.173991	1.182898	1.175991
TABLE IL Comparison of different wavelet transforms on the MR dataset								

	Wavelet transform							
Name	(2,2)	(2,4)	(4,2)	(4,4)	(2+2,2)	S+P A	S+P B	S+P C
MR_liver_t1	2.360825	2.385874	2.386182	2.385406	2.382884	2.545245	2.538325	2.515851
MR_liver_t2	1.743492	1.752467	1.720655	1.720858	1.721860	1.802205	1.767794	1.735677
MR_sag_head	2.307030	2.307953	2.308436	2.306656	2.300779	2.445971	2.489944	2.494804
MR_ped_chest	1.881426	1.882786	1.878120	1.877863	1.874376	2.193359	2.265028	2.265028

GOS size	Inter-slice levels	bpv
16	2	1.426689
32	2	1.393799
64	2	1.375358
64	4	1.382973
128	2	1.369475
128	4	1.375102

TABLE III. Comparison of different coding unit sizes and interslice levels for the CT wrist dataset

4.1. Lossy compression

Thanks to SPIHT's properties of precise rate control and idempotence, lossy coding results can be generated by setting the desired decoding bitrate once the dataset has been lossless compressed. In order to evaluate lossy performance, we consider the complete CT_skull dataset, compressed as a single coding unit. As coder parameters we choose 5 levels of intra-slice decomposition, 2 levels inter-slice decomposition, (2+2,2) intra-slice and (2,2) inter-slice integer filters. Two typical compression rates (0.1bpp and 0.5bpp) are chosen and results showing PSNR/slice are illustrated in Fig. 2.



The large PSNR variation is typical of 3D compression, as reported also in [1]. Such phenomenon depends both on image contents and transform operation. Results show that an average PSNR of 34.65dBs is obtained at 0.1bpp while a value of 41. 26dBs is obtained at 0.5bpp.

Finally, a graphic example of lossy-compressed volumes is shown in Fig. 3. A detail of slice 60 of CT_skull is compressed at 0.125bpp (left), 0.5bpp (center) and compared to the original (right). At 0.125bpp coding artifacts can be observed, but perceptual quality is still good.



Fig. 3. Example of lossy compression result for detail of slice 60 of *CT_skull*; from left: 0.125bpp, 0.5bpp and original.

5. CONCLUSIONS

In this paper we presented a new lossy to lossless volumetric coding paradigm based on integer wavelet transform and SPIHT.

A composite decomposition scheme was adopted with inter-slice packet wavelet and intra-slice dyadic tree. The 3D-SPIHTp coder has been implemented and adapted to suit the hierarchical subband structure. Issues on the refinement pass and context entropy coding were discussed to gain additional performance. Finally, the proposed scheme was comprehensively tested on a well-known dataset. Results obtained for both lossy and lossless compression are good and comparable to those of the state of the art, showing that the coder succeeds in reaching good performance for lossy to lossless compression, confirming the validity of the scheme.

6. REFERENCES

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