Multiresolution Lossy-to-Lossless Coding of MRI Objects

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Abstract. This paper proposes an object-based, highly scalable, lossy-to-lossless coding approach for magnetic resonance (MR) images. The proposed approach, called OBHS-SPIHT, is based on the well known set partitioning in hierarchical trees (SPIHT) algorithm and supports both quality and resolution scalability. It progressively encodes each slice of the MR data set separately in a multiresolution fashion from low resolution to full resolution and in each resolution from low quality to lossless quality. To achieve more compression efficiency, the algorithm only encodes the main object of interest in the input data set, and ignores the unnecessary background. The experimental results show the efficiency of the proposed algorithm for multiresolution lossy-to-lossless MRI data coding. OBHS-SPIHT, is a very attractive coding approach for medical image information archiving and transmission applications especially over heterogeneous networks.

1 Introduction

From the coding point of view, the main features required for an efficient clinical picture archiving and communications systems (CPACS) can be highlighted as follows: efficient lossy-to-lossless compression, object-based functionality and high degree of scalability support.

Volumetric medical images (e.g. MR and CT) are 3D data sets which consist of a sequence of 2D data slices. For efficient archiving and transmission of such vast amounts of data a high degree of compression is required. For instance, an uncompressed typical gray scale MR set of 58 slices of 512×512 resolution results in a data volume of 116 Mbits, and downloading such information via a 56 kbps Internet connection for a remote diagnosis purpose will take more than 35 minutes. For medical image coding lossy-to-lossless compression is required to enable the provision of appropriate services for different applications according to their sensitivity to the image quality in the diagnosis process. Since lossless compression does not degrade the image, it facilitates more accurate diagnosis, of course at the expense of lower compression ratios (i.e. higher bit rates). However, lossy compression is required to significantly reduce transmission and storage costs where the loss is not diagnostically significant.

J. Blanc-Talon et al. (Eds.): ACIVS 2006, LNCS 4179, pp. 877–886, 2006.

Over the past decade, wavelet-based image compression schemes have become increasingly important and gained widespread acceptance. An example is the new JPEG2000 still image compression standard [1, 2]. Due to the multiresolution signal representation offered by the wavelet transform, wavelet based coding schemes have a great potential to support scalability features. Among the state-of-the-art embedded wavelet coding approaches, the Set Partitioning in Hierarchical Trees (SPIHT) algorithm [3] is well known as a benchmark for its compression efficiency, full SNR scalability support and very low complexity. These features have made SPIHT very attractive for medical image coding as well [4, 5, 6]. As shown in [4], an object-based version of SPIHT (OB-SPIHT) exhibits a very competitive PSNR performance for the compression of medical images. On the other hand, research conducted by Pearlman [7] showed a very significant complexity reduction of SPIHT over JPEG2000. Although the SPIHT bitstream is tailored for full SNR scalability and is progressive (by quality) coding, which can support lossy to lossless decoding, it does not support spatial scalability to provide a bitstream that can be parsed for multiresolution decoding by different clients with different capabilities.

Often there are regions inside a medical image that contain the main information required for diagnostic purposes. An object-based coding is desirable to enable coding of any region of interest with arbitrary shape in the image, separately from the other parts of the image. This feature helps to achieve a very high compression ratio by only focusing on the important regions in the image and discarding the non-important background that usually takes a large area of medical images, or by encoding the background at a lower precision with a lossy image coder [4, 8]. The region of interest (ROI) coding feature in the JPEG-2000 standard considers the whole image for coding but it applies a higher coding precision to the ROI [9, 10, 11]. On the other hand, an object-based coding makes it possible to encode the ROI as a separate object regardless of the rest of the image.

This research proposes an object-based medical image coding system based on the highly scalable set partitioning in hierarchical trees (HS-SPIHT) algorithm. The HS-SPIHT, introduced by the authors of this paper in their previous works [12, 13], is a modification of the SPIHT algorithm [3] that adds spatial scalability features to the SPIHT algorithm without sacrificing the interesting features of the original algorithm. The coding system proposed in this paper, called OBHS-SPIHT, extends the 2D HS-SPIHT algorithm to object-based coding of MRI data. The OBHS-SPIHT algorithm fulfills all the highlighted requirements for medical image information archiving and transmission systems mentioned earlier in this section.

The rest of this paper is organized as follow. Section 2 gives an overview of the OBHS-SPIHT coding system. In Section 3, the OBHS-SPIHT coding algorithm is presented. The scalable structure of the OBHS-SPIHT bitstream is explained in Section 4. In Section 5, some details about the simulation of the coding system are given and experimental results for multiresolution lossless as well as lossy decoding are presented, and finally, Section 6 concludes the paper.

2 System Overview

The proposed OBHS-SPIHT coding system is depicted in Figure 1. The system input is volumetric MR data set which consists of various slices. On the encoder side, each

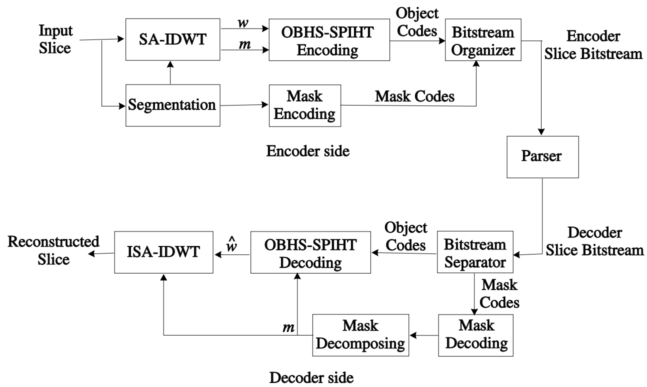

Fig. 1. Block diagram of the OBHS-SPIHT coding system. w denotes the wavelet coefficients, and m means the decomposed mask.

slice is first segmented to extract the medical object of interest from the background. Each voxel in the data set is considered either inside or outside the object. The extracted object is decomposed by a shape-adaptive integer DWT (SA-IDWT) approach which maps integer object voxels to integer wavelet coefficients. Details on the segmentation process and the DWT will be given in Section 5.

The decomposed object coefficients and the decomposed shape mask are then consigned to the OBHS-SPIHT encoder. The encoder only encodes the coefficients that belong to the decomposed object. To recognize these coefficients it uses the decomposed shape mask. The bitstreams from the shape coding and object coding algorithms are assembled in the bitstream organizer to generate the final encoder output bitstream.

In a customization stage, the encoded bitstream is reordered and truncated by a parser which provides proper bitstreams for multiscale lossy-to-lossless decoding. On the decoder side, the bitstream separator first extracts the mask and the object bitstreams from the parsed bitstream. The shape mask is then reconstructed by decoding the shape bitstream. The decomposed mask, which is required by the OHS-SPIHT decoder, is provided by applying the same level of decomposition as used by the encoder to the shape mask. The OHS-SPIHT decoder then decodes the object bitstream, and the inverse SA-DWT is applied to the decoded wavelet coefficients to reconstruct the original slice object at the requested resolution and rate.

3 Object-Based HS-SPIHT

The SPIHT algorithm of [3] considers sets of coefficients that are related through the parent-offspring dependency depicted in Figure 2. In its bitplane coding process, the algorithm deals with the wavelet coefficients as either members of insignificant sets, individual insignificant pixels, or significant pixels. It sorts these coefficients in three ordered lists: the list of insignificant sets (LIS), the list of insignificant pixels (LIP),

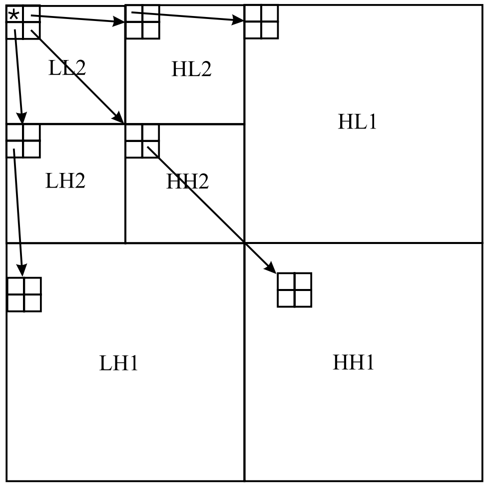

Fig. 2. 2D SPIHT Parent-offspring dependency across wavelet subbands in each slice

and the list of significant pixels (LSP). The main concept of the algorithm is managing these lists in order to efficiently extract insignificant sets in a hierarchical structure and identify significant coefficients, which is the core of its high compression performance. The SPIHT algorithm provides a progressive (by quality) bitstream which is fully SNR scalable, however its bitstream does not support spatial scalability.

In [12, 13] we proposed a scalable modification of SPIHT for image coding, called highly scalable SPIHT (HS-SPIHT), through the introduction of multiple resolution-dependent lists and a resolution-dependent sorting pass. In general, a wavelet decomposed slice with N levels of 2D decomposition enables a scalable encoder to provide at most $N+1$ different spatial resolution levels. To distinguish between different resolution levels, we denote the lowest spatial resolution level as level $N+1$. The spatial resolution related to level k is $1/2^{k-1}$ of the resolution of the original data set. The full resolution (the original sequence) then becomes level 1. The three subbands (HL_k, LH_k, HH_k) that need to be added to increase the spatial resolution from Level $k+1$ to Level k are grouped and called spatial subband set level k. The HS-SPIHT algorithm encodes the different resolution subbands in the wavelet decomposed image separately, allowing a parser or a decoder to directly access the data needed for reconstruction of a desired spatial resolution and/or quality. To manage the scalable coding process, for each resolution subband set, the algorithm defines a set of LIP, LSP and LIS lists, therefore there are LIP_k, LSP_k, and LIS_k for $k = s_{max}, s_{max}-1, \ldots, 1$ where s_{max} is the maximum number of spatial resolution levels supported by the encoder. To improve the algorithm to be used for coding of medical images which contain objects with any arbitrary shape, we only consider and process those coefficients that belong to the decomposed object (see Figure 3) and those sets that are at least partially located inside the decomposed object, similar to the SA-SPIHT algorithms in [14].

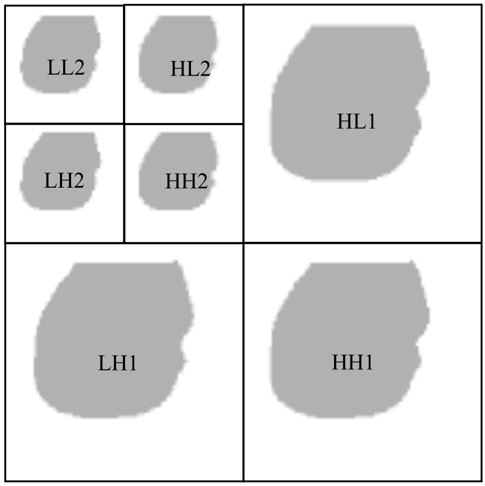

Fig. 3. Example of a decomposed mask of an arbitrarily shaped object

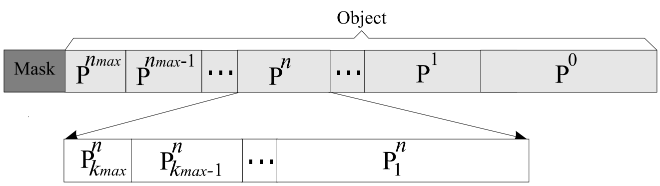

Fig. 4. Structure of the OBHS-SPIHT encoder bitstream for a slice. P_k^n is related to the codepart of spatial subband set level k at bitplane level n.

4 Bitstream Structure

Figure 4 shows the structure of the bitstream generated by the OBHS-SPIHT encoder for a slice. The scalable object bitstream is constructed of different codeparts (P^n), where each part belongs to a bitplane level. Inside each bitplane codepart, the bits that belong to the different spatial subband sets, P_k^n, are separable. To support bitstream parsing, some markers are put in the bitstream to provide the information required for identifying the different resolution and bitplane codeparts in the parsing process.

The encoder needs to encode the input object only once at a lossless rate (covering all biplane coding levels from the maximum bitplane level to bitplane level 0). Different bitstreams for different spatial resolutions can be easily generated from the encoded bitstream by selecting the related resolution codeparts. The parsing process is a simple codeparts-selection procedure and can be carried out by a server that stores the encoded medical data sets or by an individual parser as a part of an active network. The parser does not need to decode any part of the bitstream. As a distinct feature, the reordered bitstreams for each spatial resolution are completely rate-embedded (fine granular at bit

Table 1. Description of the MR data sets used as test volumetric medical images in this paper

History	Age	sex	File name	Voxel size (mm)	Volume size
Congenital heart disease	1	M	MR_ped_chest	$0.78 \times 0.78 \times 5$	$256 \times 256 \times 77$
Normal	38	F	MR_liver_t	$1.45 \times 1.45 \times 5$	$256 \times 256 \times 58$
Normal	38	F	MR_liver_t2e1	$1.37 \times 1.37 \times 5$	$256 \times 256 \times 58$
Left exopthalmos	42	M	MR_sag_head	$0.98 \times 0.98 \times 3$	$256 \times 256 \times 58$

level) and can be truncated at any point up to the level of a perfect lossless reconstruction. Note that the markers in the main bitstream are only used by the parser and do not need to be sent to the decoder.

5 Experimental Results

5.1 Simulation Details

The OBHS-SPIHT coding system were fully software implemented. As volumetric medical data we have chosen the four gray-scale (8 bits per voxel) MR data sets that were also used in [6,5,15]. A description of these MR sets is given in Table 1. To extract the objects from the unimportant, very low magnitude background voxels, a two-stage threshold-based segmentation scheme was used. In the first stage, each MR set was compared with a threshold and all voxels that exceeded the threshold were considered to belong to the object. In a second stage, all background areas that were surrounded by the object were reclassified to belong to the object. The first slice of one of the MR test set, MR_sag_head, and its appropriate segmentation mask is shown in Figure 5. For the object-based wavelet decomposition, an efficient, non-expansive SA-DWT approach, based on the method introduced in [16] was implemented. The integer I(2,2) wavelet filter bank [17] was implemented in a lifting scheme and used for object decompositions with symmetric extension at the boundaries of the object in each slice.

The OBHS-SPIHT encoder was set to progressively encode the decomposed objects of all slices of each MR test set to the lossless rate with three levels of spatial scalability support. The binary mask information for each slice was encoded by an arithmetic binary coding scheme [18].

5.2 Results

Table 2 provides the average bits per voxel (bpv) obtained by OBHS-SPIHT for multiresolution lossless coding of the four MR object sets. As the results show for both cases, a lossless version of the lower resolutions can be obtained at very small rates. Figure 6 shows the lossless reconstruction of slice 9 of MR_sag_head data set at three different resolutions (full, half and quarter). The average rate consumed for coding of the binary mask information of the MR sets lies between 0.016 bpv to 0.02 bpv and therefore negligible.

In Table 3, the OBHS-SPIHT results for lossless coding at full resolution are compared with HS-SPIHT, SPIHT, JPEG2000, JPEG-LS and WinZip coding approaches.

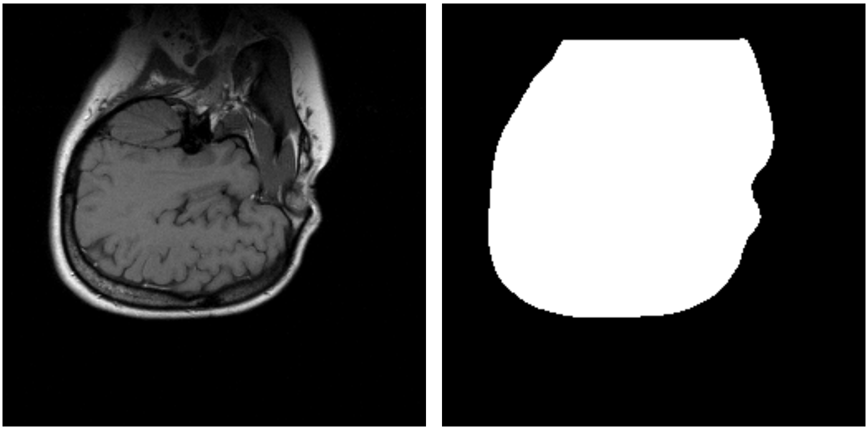

Fig. 5. The first slice of the MR_sag_head data set. (a) Original data. (b) Extracted mask.

Table 2. Average bits per voxel obtained for lossless encoding of the MR data sets by OBHS-SPIHT

Spatial resolution	lossless bits per voxel (bpv)			
	MR_ped_chest	MR_liver_t1	MR_liver_t2e1	MR_sag_head
Quarter	0.1419	0.2722	0.2605	0.1727
Half	0.4339	0.8320	0.8378	0.5435
Full	1.2550	2.3420	2.4955	1.7440

For these coding approaches, the object background in all slices was set to zero to have a fair comparison with OBHS-SPIHT. A very small difference between the lossless compression rates of HS-SPIHT and SPIHT is due to the extra budget consumed by HS-SPIHT for markers in the bitstream which are required for the parsing process. The results reported here for SPIHT, HS-SPIHT and OBHS-SPIHT were obtained without extra arithmetic coding of the encoder output bitstreams. As shown in [3], an improved coding performance for SPIHT and consequently for HS-SPIHT can be achieved by further compressing the binary bitstreams with an arithmetic coder. Despite this fact, the OBHS-SPIHT algorithm provides comparable results to JPEG2000 while it has much less complexity [7]. As the results show, JPEG-LS outperforms the other coders, but it does not support spatial scalability and its bitstream can not be used for lossy decoding.

To show the full scalability of OBHS-SPIHT, Table 4 presents some numerical results for multiresolution decoding of the MR test sets at a wide range of bit rates. This is based on a scenario of one-time-encoding and multiple-times-decoding, by parsing the encoder bitstream for various resolutions and rates, which is required for serving different clients with different capabilities in archiving and transmission systems especially over a heterogeneous system like the Internet. In such systems each client can request a specific bit rate and resolution level which fits its needs.

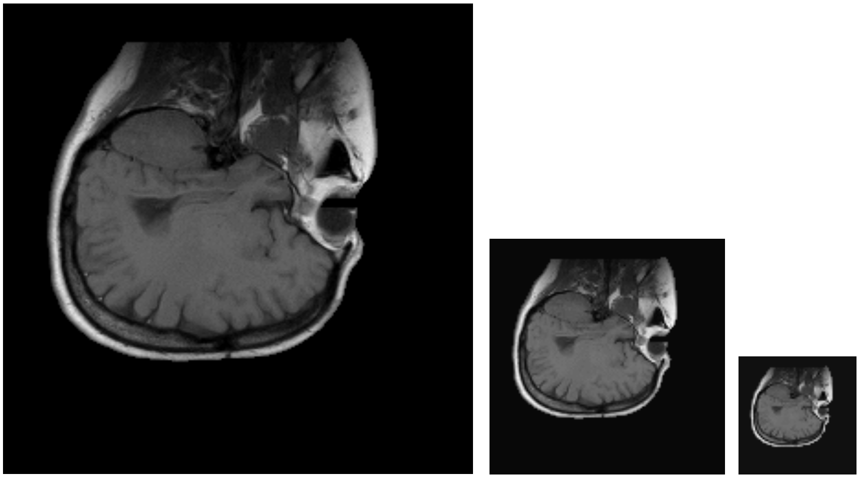

Fig. 6. Lossless reconstruction of slice 9 of MR_sag_head at full, half and quarter resolution by OBHS-SPIHT decoder

Table 3. Comparison of average bits per voxel obtained for lossless encoding of the MR data sets at full resolution with different coding methods

Method	MR_ped_chest	MR_liver_t1	MR_liver_t2e1	MR_sag_head
OBHS-SPIHT	1.2550	2.3420	2.4955	1.7440
HS-SPIHT [12]	1.5921	2.6354	2.7781	2.1772
SPIHT [3]	1.5818	2.6247	2.7677	2.1660
JPEG2000 [19]	1.4537	2.2266	2.3499	1.9029
JPEG-LS [20]	1.2183	1.9587	2.1134	1.5911
WinZip	1.8900	3.7261	3.7512	2.3571

Table 4. PSNR results for lossy decoding of the OBHS-SPIHT bitstreams at different spatial resolutions and rates

Spatial resolution	rate (bpv)	PSNR (dB)			
		MR_ped_chest	MR_liver_t1	MR_liver_t2e1	MR_sag_head
Quarter	0.0625	45.72	35.65	35.59	42.84
	0.125	58.26	45.37	45.58	53.70
Half	0.0625	33.56	28.79	27.62	32.70
	0.125	40.43	33.88	31.96	38.45
	0.25	48.00	40.26	38.85	44.75
Full	0.125	32.42	28.13	25.67	30.55
	0.25	36.72	32.96	29.90	34.33
	0.5	42.23	37.03	34.89	38.43
	1	47.70	43.05	40.24	43.47

6 Conclusions

An object-based, highly scalable wavelet coding system, OBHS-SPIHT, for lossy-to-lossless coding of MR data was presented. The object of interest in each slice of MR data sets were segmented from the background. A reversible shape-adaptive integer DWT was used to decompose the input objects. Each slice of the data set was encoded separately. This not only facilitates more efficient random access to the slices, but also requires less memory from the coding system. The OBHS-SPIHT bitstream is easily reorderable by a simple parser for multiresolution decoding. The experimental results for lossy and lossless cases on some MR data sets at various spatial resolution levels showed the excellent performance of the proposed algorithm. Possessing important features such as arbitrarily shaped object coding and full resolution and quality scalability functionalities makes the proposed approach attractive for volumetric medical image information archiving and transmission systems.

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