3-D WAVELET CODEC (COMPRESSION/DECOMPRESSION) FOR 3-D MEDICAL IMAGES

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ABSTRACT

Compression is an important part in image processing in order to save memory space and reduce the bandwidth while transmitting. The main purpose of this paper is to analyse the performance of 3-D wavelet encoders using 3-D medical images. Four wavelet transforms, namely, Daubechies 4,Daubechies 6,Cohen-Daubechies-Feauveau 9/7 and Cohen Daubechies-Feauveau5/3 are used in the first stage with encoders such as 3-D SPIHT,3-D SPECK and 3-D BISK used in the second stage for the compression. Experiments are performed using medical test image such as magnetic resonance images (MRI) and X-ray angiograms (XA). The XA and MR image slices are grouped into 4, 8 and 16 slices and the wavelet transforms and encoding schemes are applied to identify the best wavelet encoder combination. The performances of the proposed scheme are evaluated in terms of peak signal to noise ratio and bit rate.

KEYWORDS

Medical image Compression, 3-D SPIHT, 3-D SPECK and 3-D BISK, Symmetric Wavelet Transform, Decoupled wavelet transform.

1. INTRODUCTION

Digital image processing [23] allows one to enhance image features of interest why attenuating detail irrelevant to a given application, and then extract useful information about the scene from the enhanced image. Image compression addresses the problem of reducing the image storage/transmission requirements. Lossless image compression involves with compressing images which, when decompressed, will be an exact replica of the original image. This is the case when important information like medical images is involved. They need to be exactly reproduced when decompressed. The basic task of digital image processing in medicine is source image enhancement. Images received from various medical devices(X-ray, magnetic Resonance Imaging(MRI),X-Ray based Computer Tomography(CT) usually not very clear and containing noise-are filtered by using low level image processing algorithms(de-noising,sharpening,edge detection) with parameter values tweaked for the specific problem and enlarging the amount of useful information offered to the medical specialist that interprets it. Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) is a medical imaging technique used in radiology to visualize internal structures of the body in detail. Angiography or arteriography is a medical imaging technique used to visualize the inside, or lumen of blood vessels and organs of the body, with particular interest in the arteries, veins and the heart chambers. Rotational angiography is a medical imaging technique based on x-ray that allows acquiring CT-like 3D volumes during hybrid surgery or during a Cather intervention using a fixed C-Arm.

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The fundamental components of compression are redundancy and irrelevancy reduction. There are three types of redundancy can be identified: (i) Spatial Redundancy is the correlation between neighbouring pixel values. (ii) Spectral Redundancy is the correlation between different colour planes or spectral bands. (iii) Temporal Redundancy is the correlation between adjacent frames in a sequence of images.

Image compression focuses on reducing the number of bits needed to represent an image by removing the spatial, spectral and temporal redundancies. An ideal 3-D medical image compression algorithm should support both progressive transmission and random access. A volumetric medical image corresponds to a 3-D grid of samples or voxels. Over the past few years, variety of powerful and sophisticated wavelet-based schemes for image compression, have been developed and implemented. Wavelet compression methods have produced superior objective and subjective results. With wavelets compression rate of up to 1:300 is achievable. Wavelet compression allows the integration of various compression techniques into one algorithm.

This paper focuses onto make analyse the different discrete wavelet transform algorithms like 3-D SPIHT, 3-D SPECK and 3-D BISK, Symmetric Wavelet Transform, Decoupled wavelet transform. The rest of the paper is organized as follows. In Section 2, discuss the related work. In section 3, explains the proposed work. In Section 4, the experimental result is given. Finally conclusion is presented in section 5 of the paper.

2. RELATED WORK

A new compression method was proposed to exploit the quad tree and block-based coding concepts, layered zero-coding principles, and context-based arithmetic coding and the performances of these coders were compared with those of the JPEG2000, 3-D SPIHT and 3-D SPECK. It has shown that in the case of lossless compression, the proposed coders give excellent results whereas for lossy compression it provides comparable results [3].

They Modified the 3-D SPIHT and the 3-D EBCOT coding schemes and applied them for compressing the medical data and showed that their method gives comparable results for both lossy and lossless compression [5]. An optimal 3-D co-efficient tree structure for 3-D zero tree wavelet video coding was proposed and they showed that the 3-D zero tree coding need not be applied symmetrically along all the directions and that the asymmetrical trees can produce higher compression ratio than the symmetrical ones[11].They had incorporated the region of interest(ROI) detection stage and texture modelling stage into the 3-D wavelet and SPIHT framework.3-D SPECK and 3-D binary set splitting with k-D trees(3-D BISK) have been used mostly for compression of hyper spectral images[12]. They had shown that 3-D SPECK gave comparable performance to that of the 3-D SPHIT coder [13]. They had shown that the performances of the different techniques are roughly similar in terms of rate distortion performance [14]. The OB-SPECK algorithm(Object based set partitioned embedded block coder)for wavelet coding of arbitrary shaped video object was used. The proposed scheme achieved high coding efficiency and preserved the features of an embedded bit stream, low computational complexity and exact bit rate control[15]. 3-D BISK for shape adaptive coding of ocean-temperature data was proposed and the performance of 3-D BISK were compared to prominent shape-adaptive coders and superior performance was reported[16]. Although several work have been reported for 3-D medical image compression using wavelets, optimal wavelets coders suitable for medical image compression problems has not been explored.

3. PROPOSED WORK

This work discusses the performance evaluation of 3-D wavelet codec using 3-D medical images. Four wavelet transforms, namely, Daubechies 4, Daubechies 6, Cohen-Daubechies-Feauveau 9/7 and Cohen Daubechies-Feauveau5/3 are used in the first stage with encoders such as 3-D SPIHT,3-D SPECK and 3-D BISK used in the second stage for the compression. Experiments are performed using medical test image such as magnetic resonance images (MRI) and X-ray angiograms (XA) test images. The performances of the 3-D medical images are evaluated in terms of peak signal-to-noise ratio (PSNR) and bit rate and the optimal wavelet transform-encoder is identified. Figure 1 shows the block diagram for the compression technique using the 3-D wavelet encoders. First the 3-D medical image is split into group slices (GOS).Then the 3-D wavelet transform is applied, followed by 3-D encoding.

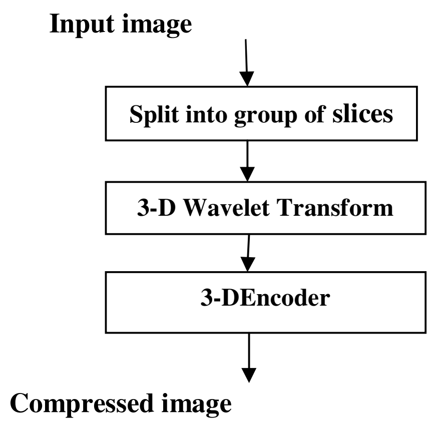

Figure 1.Block diagram of the 3-D wavelet transform based storage/transmission.

The 3-D wavelet transform can be obtained by applying 1-D wavelet transform along each dimension. If Wx, Wy, Wz represent the wavelet transformations applied along the x, y and z axes then transform of this image is defined as $W=(WxWyWz)_1(WxWyWz)_{2.} \ldots (WxWyWz)_{L.}$ where L is the number of levels. This is called the 3-D symmetrical wavelet transformation, where all the dimensions are decomposed to equal number of levels by applying wavelet transform alternately to each axis in figure 2. [11].On the other hand,3-D wavelet transform can be also be obtained by applying 2-D spatial transform first, followed by wavelet transform on the z axis separately. The spatial axis are decomposed to equal number of levels 'L' but the z axis can be decomposed to 'l' levels which need not be equal to 'L'. This is called the decoupled 3-D wavelet transform or the 3-D wavelet packet transform[11].The lifting approach for implementing wavelets is used here[17].3-D DWT can be realized by applying 1-D DWT along each dimension. For i-D wavelet lifting, the input signal is split into and odd and even samples followed by a series of predict(P) and update(U) lifting steps to obtain the low pass(LP) and high pass(HP)coefficients respectively[18].The predict and update steps are sometimes referred to as dual and primal lifting steps. The inverse transform is formed by reversing the steps of the forward transform and flipping the signs.

3.1. Overview of encoding schemes

3.1.1. 3-D SPIHT Encoding

The SPIHT encoding technique was developed by Said and Pearlman in1996.It uses a data structure called the spatial orientation trees (SOT).This algorithm searches each tree, and divides the three lists:

- The list of significant pixels (LSP) containing the coordinates of pixels found to be significant for the current threshold.
- The list of insignificant pixels (LIP),with pixels that are not significant for the current threshold and
- The list of insignificant sets (LIS), which contain information about trees that have all the constituent entries to be insignificant at the current threshold.

3-D SPIHT algorithm is based on three basic concepts:

1. Code/transmit important information first based on the bit-plane representation of pixels.
2. Ordered refinement bit-plane transmission, and
3. Coding is done along the predefined path/trees called spatio-temporal orientation trees, which resourcefully exploit the properties of a 3-D wavelet transformed image.

3-D consists of two main stages: sorting and refinement. In sorting stage, 3-D SPIHT sorts' pixels by magnitude with respect to a given threshold, which is a power of two, also called the levels of significance. The sorting is based on the significance test of pixels along the spatio-temporal orientation trees rooted from the highest level of the pyramid in the 3-D wavelet transformed image. Spatio-temporal orientation trees were introduced to test significance of groups of pixels for efficient compression by exploiting self-similarity and magnitude localization properties in a 3-D wavelet transformed image. The basic function of actual sorting algorithm is to recursively partition sets in the LIS to locate individually significant pixels, insignificant pixels, and smaller insignificant sets and move their co-ordinates to the appropriate lists, the LSP, LIP and LIS respectively [27].After each sorting stage, 3-D SPIHT outputs refinement bits at the current level of bit significance of those pixel which had been moved to the LSP at higher thresholds. In this way, the magnitude of significant pixels is refined with the bits that decrease the error the most. This process continues by decreasing the current threshold successively by factors of two until the desired bit-rate or image quality is reached [28].

3.1.1. 3-D SPECK

Consider a hyper spectral image sequence which has been adequately transformed using the discrete wavelet transform. The transformed image sequence is said to exhibit a hierarchical pyramidal structure defined by the levels of decomposition, with the topmost level being the root. The finest pixels lie at the bottom level of the pyramid while the coarsest pixels lie at the top level. The image sequence is represented by an indexed set of transformed coefficients $C_{i,j,k}$, located at pixel position (i, j, k)* in the transformed sequence.

Pixels are grouped together in sets which comprise regions in the transformed images. We say a set S is significant with respect to n, if the condition given in equation (1),

$$\mathrm{Max}_{i,j,k \in S} | C_{i,j,k} | \geq 2^n \qquad \ldots (1)$$

Where $C_{i,j,k}$ denotes the transformed coefficients at coordinate (i, j, k). Otherwise it is insignificant. For convenience, we can define the significance function of a set S is given in equation (2) as:

$$T_n(S) = \begin{cases} 1: \text{ if } 2^n \leq \max_{i,j,k \in S} | C_{i,j,k} | < 2^{n+1} \\ 0: \text{ else} \end{cases} \qquad \ldots..(2)$$

3-D SPECK makes use of rectangular prisms in the wavelet transform. Each sub band in the pyramidal structure is treated as a code block or prism, henceforth referred to as sets S, and can be of varying dimensions. The dimension of a set S depends on the dimension of the dimension of the original images and the sub band level of the pyramidal structure at which the set lies. We define the size of a set to be the number of elements in the set.

3-D SPECK maintains two linked lists:

- **LIS**-List of Insignificant Sets. This list contains S sets of varying sizes.
- **LSP**-List of Significant pixels. This list contains pixels that have been found significant against a certain threshold [13].

The main body of 3-D-SPECK consists of four steps: the initialization step; the sorting pass; the refinement pass; and the quantization step.

3.1.2.3-D BISK

Binary set splitting of k-d trees (BISK) allows more flexible coding of arbitrarily shaped regions. 3D-BESK does aggressive shrinking of the sets to the bounding box of the coefficients contained in the set, which is responsible for a large part of the performance gain. Octrees and k-d trees are two well-known methods for the partitioning of 3-D sets. In a k-d tree, a set is divided along a single dimension into two arbitrarily sized subsets.

Figure 3.Set partitioning in 3D-BISK.

Figure 3.depict set partitioning of BISK in 3D.Utilizing k-d trees for set partitioning allows us to extend BISK to higher dimensions without significantly increasing the implementation complexity. It is straightforward to see that k-d trees can achieve a partitioning of a set identical to that resulting from octree decomposition, although usually a greater number of levels of decomposition are needed.

Following a 3D wavelet transform, the BISK algorithm initiates by splitting the set of transform coefficients, X, in to individual sub bands S which are then placed in a list of insignificant sets(LIS).This follows the common bit plane-coding paradigm consisting of sorting and refinement passes. In the sorting pass it determines the significance of a set by comparing the largest opaque coefficient magnitude contained in the set to the current threshold. When a set has no significant coefficient, then it is placed in the LIS, and, during the sorting pass, a significance test is done for each set in the LIS against the current threshold. If the set becomes significant, then the set is split into two according to the k-d tree decomposition structure. The two new sets are placed into an LIS, recursively tested for significance, and split again if needed. At any time, if a set contains no opaque coefficients, then it is removed from its LIS and discarded.

4. EXPERIMENTAL RESULTS

The 3-D medical image data considered in this work are MR and XA images. Samples of MR and XA images with all the 16 slices are shown in Figure 4.

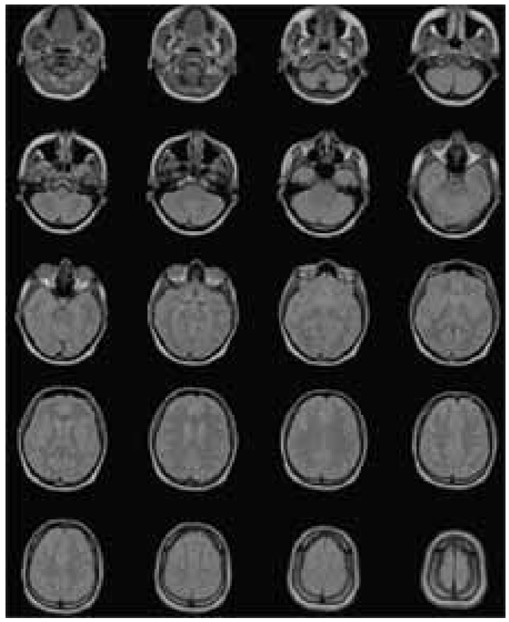

Figure 4. (a) Sample of MR image

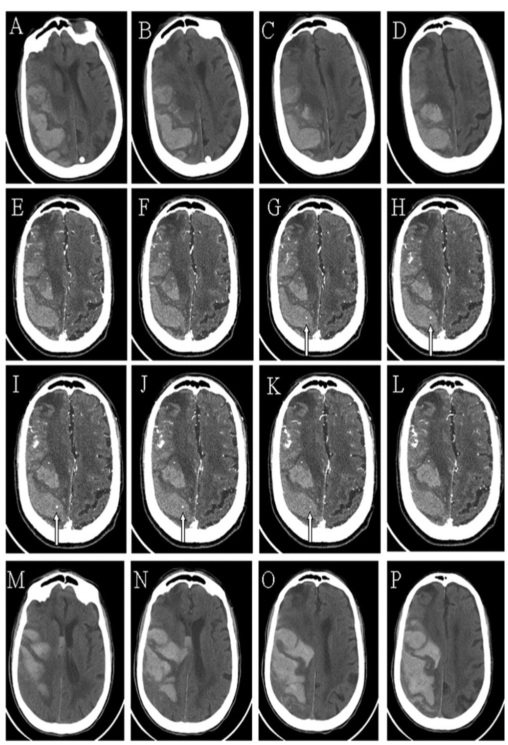

Figure 4. (b) Sample of XA image.

The slices in each GOS are chosen as 4, 8 and 16.The numbers of decompositions for the symmetric and the decoupled wavelet transform are given Table 1.

Table 1. Number of decomposition level.

Wavelet Transform	GOS	No. of spatial decomposition		No. of temporal decompositions
	MR (256X256)	XA (512X512)	(MR & XA)	
Symmetric	4	1	1	1
8	2	2	2	
10	3	3	3	
Decoupled	4	7	8	1
8	7	8	2	
16	7	8	3	

Error E = *Original image – Reconstructed image*

MSE = *E / (SIZE OF IMAGE)*

PSNR is the ratio between signal variance and reconstruction error variance. PSNR is usually expressed in Decibel scale. The PSNR is mostly used as a common measure of the quality of reconstruction in image compression etc.

$$\textbf{PSNR} = 20 \log_{10} (255 / \text{sqrt}(\text{MSE}))$$

Here 255 represent the maximum pixel value of the image, when the pixels are represented using 8 bits per sample. PSNR values range between infinity for identical images, to 0 for images that have no common all it. PSNR is inversely proportional to MSE and CR as well, that is PSNR decreases as the compression ratio increases, for an image.

CR is defined as the ratio between the original image size and compressed image size.

Compression ratio = *original Image size ÷ compressed Image size*

Bit rate is an average bits required to represent a single sample (pixel) in the compressed image. The standard value of the bit rate for image is 8 bits per pixel (bpp). The bit rate is defined in Equation,

BPP = *Size of the compressed file ÷ total number of pixel*

Table 2 shows that the better result when the number of slices is more the decoupled wavelet transform and Daubechies 4(DB 4) wavelet in the first stage with 3-D SPIHT encoder in the second stage has been identified as the optimal wavelet-encoder for the compression of 3-D medical images.

Table 2. Compression results of GOS with 16 slices for XA images.

3-D encoder rate	Bit CDF 9/7	Decoupled			
		CDF 5/3	D4	D6	
SPIHT	0.1	23.03	22.73	23.08	23.11
0.5	25	23.69	25.21	25.28	
1	26.86	24.9	27.19	27.3	
1.5	29.59	26.86	30.15	30.26	
2	32.14	30.09	32.63	32.67	
3	38.19	36.02	38.74	38.77	

Table 3 shows that the better performance of GOS with 16 slices in Decoupled wavelet transform and Daubechies 4(D4) with 3-D SPIHT in MR images compared with other transforms.

Table 3. Compression results for GOS of 16 slices of MR images.

3-D encoder Rate	Bit CDF 9/7	Decoupled			
		CDF 5/3	D4	D6	
SPIHT	0.1	1.48	21.35	21.51	21.51
0.5	23.26	22.55	23.4	23.4	
1	25.94	24.89	26.21	26.16	
1.5	28.56	26.73	28.91	28.87	
2	32.12	30.51	32.55	32.37	
3	38.58	36.6	39.08	38.75	

5. CONCLUSION

This work discusses the performance evaluation of 3-D wavelet codec (Compression/decompression) for 3-D medical images. It has been found from the experimental results that the decoupled wavelet performs better than symmetric wavelet transform. When the number of slices is more the decoupled wavelet transforms provides good results. So it is useful for MR and XA images where the number of slices is usually large and the quality of image becomes an important criterion. It can be concluded that the Daubechies 4(DB 4) wavelet in the first stage with 3-D SPIHT encoder in the second stage has been identified as the optimal wavelet-encoder for the compression of 3-D medical images. The GOS consisting of 16 slices was found to be the optimum GOS.

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