Scalable Compression of 3-D Medical Image Data Using EBCOT with Volume of Interest Coding

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***Abstract* - Volumetric medical image data usually require a vast amount of resources for storage and transmission. With the wide pervasiveness of medical imaging applications in healthcare settings and the increased interest in telemedicine technologies, it has become essential to reduce both storage and transmission bandwidth requirements needed for archival and communication of related data, preferably by employing lossless compression methods to avoid any negative effects of lossy compression on image quality and diagnostic capabilities. The main objective is to present a 3-D medical image compression method with scalability properties, by quality and resolution up to lossless reconstruction and optimized Volume of Interest (VOI) coding at any bit-rate. The proposed method named as "EBCOT with VOI coding" employs a 3-D integer wavelet transform (3D-IWT) and a modified EBCOT with 3-D contexts to compress the 3-D medical imaging data into a layered bit-stream that is scalable by quality and resolution. VOI coding capabilities are attained after compression by employing a bit-stream reordering procedure, which is based on a weight assignment model that incorporates the position of the VOI and the mean energy of the wavelet coefficients. Optimized VOI coding at any bit-rate is attained by an optimization technique that maximizes the reconstruction quality of the VOI, while allowing for the decoding of background information with peripherally increasing quality around the VOI. Performance evaluations based on real 3-D medical imaging data showed that the proposed method achieves a higher reconstruction quality, in terms of the peak signal-to-noise ratio, than that achieved by 3D-JPEG2000 with VOI coding, when using the MAXSHIFT and general scaling-based methods.**

***Keywords* - Embedded block coding with optimized truncation (EBCOT), Integer wavelet transform, medical image compression, scalable compression, volume of interest coding, 3D-JPEG2000**

I. Introduction

Most of the current medical imaging techniques produce three-dimensional (3-D) data distributions. Some of them are intrinsically volumetric, like magnetic resonance (MR), computerized tomography (CT), positron emission tomography (PET), and 3-D ultrasound. Such 3-D data usually require a vast amount of resources for storage and transmission. As the amount of 3D medical images generated increases, the storage, management, and access to these large repositories is becoming increasingly complex. This also requires various bandwidth capabilities for transmission over networks.

With the wide pervasiveness of medical imaging applications in healthcare settings and the increased interest in telemedicine technologies, it has become essential to reduce both storage and transmission bandwidth requirements needed for archival and communication of related data, preferably by employing lossless compression methods. Furthermore, providing random access as well as resolution and quality scalability to the compressed data has become of great utility. Random access refers to the ability to decode any section of the compressed image without having to decode the entire data set. Resolution and quality scalability, on the other hand, refers to the ability to decode the compressed image at different resolution and quality levels, respectively. The latter is especially important in interactive telemedicine applications, where clients (e.g., radiologists or clinicians) with limited bandwidth connections using a remote image retrieval system may connect to a central server to access a specific region of a compressed 3-D data set, i.e., a volume of interest (VOI).

3-D image data can be represented as multiple two-dimensional (2-D) slices; it is possible to code these 2-D images independently on a slice-by-slice basis. Several excellent 2-D lossless compression algorithms, such as lossless image-compression standard JPEG-LS and the context-based adaptive lossless image codec (CALIC) algorithm do not exploit the dependencies that exist among pixel values in all three dimensions. Because pixels are correlated in all three dimensions, a better approach is to consider the whole set of slices as a single 3-D data set. Several methods that utilize dependencies in all three dimensions have been proposed. Some of these methods use the 3-D discrete wavelet transform in a lossy compression scheme, whereas others use predictive coding in lossless schemes.

Several compression methods for 3-D medical images have been proposed in the literature, some of which provide resolution and quality scalability up to lossless reconstruction [1]–[3]. These methods are based on the discrete wavelet transform (DWT), whose inherent properties produce a bit-stream that is resolution-scalable. Quality scalability is then achieved by employing bit-plane based entropy coding algorithms that exploit the dependencies between the location and value of the wavelet coefficients, such as the embedded zerotree wavelet coding (EZW), the set partitioning in hierarchical trees (SPIHT), and the embedded block coding with optimized truncation (EBCOT) algorithms [4]–[6]. These compression methods, however, do not provide VOI decoding capabilities.

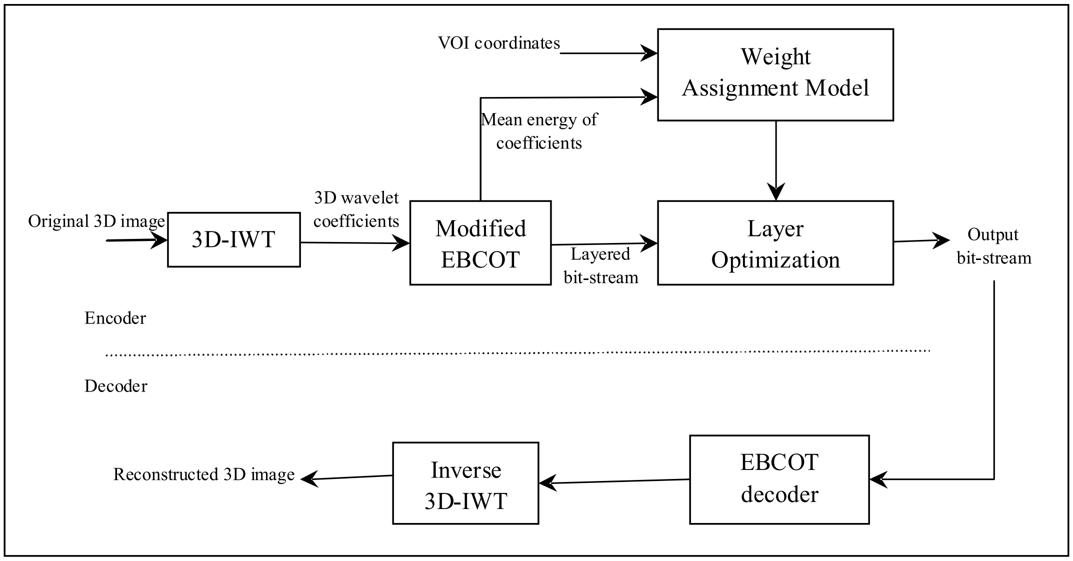

Fig. 1. Block diagram of the proposed scalable lossless compression method

Recently, a number of medical image compression methods that support VOI coding have been proposed [8]–[10]. In [8], the authors introduced a 3-D medical image compression technique that supports VOI coding based on 3-D sub-band block hierarchical partitioning (3D-SBHP), a highly scalable wavelet transform based entropy coding algorithm. A number of parameters that affects the effectiveness of VOI coding including the size of the VOI, the number of decomposition levels, and the target bit-rate. The authors also discussed an approach to optimize VOI decoding by assigning a decoding priority to the different wavelet coefficient bit-planes. In [8], the authors summarized the features of various methods for VOI coding, including the maximum shift (MAXSHIFT) and general scaling-based (GSB) methods supported by the JPEG2000 standard [11]. These particular methods scale up the coefficients associated with a VOI above the background coefficients, by a scaling value. In [10], the authors presented a VOI coding method for volumetric images based on the GSB method and the shape-adaptive wavelet transform. The method extends the capabilities of the GSB method to 3-D images with arbitrarily-shaped VOIs and allows for coding partial background information in conjunction with the VOI.

The main objective of this paper is to present a 3-D medical image compression method with 1) scalability properties, by quality and resolution up to lossless reconstruction and 2) optimized VOI coding at any bit-rate. It is mainly concerned in interactive telemedicine applications, where different remote clients with limited bandwidth connections may request the transmission of different VOIs of the same compressed 3-D image stored on a central server. In this work, the VOI is a cuboid defined in the spatial domain with possibly different values for the length, width and height.

The proposed method is different from the VOI coding method proposed in [8], where the background information is only decoded after the VOI is fully decoded, which prevents observing the position of the VOI within the original 3-D image. The proposed method also differs from the method in [10], where the scaling value of the VOI coefficients is empirically assigned and the shape information of the VOI must be encoded and transmitted, which may result in an increase in computational complexity as well as bit rate (due to shape encoding). The proposed method will achieve a higher reconstruction quality, in terms of the peak signal-to-noise ratio (PSNR), than those achieved by 3D-JPEG2000 with VOI coding at a variety of bit-rates.

The performance of the proposed method is compared with 3D-JPEG2000 with VOI coding, using the MAXSHIFT and the GSB methods. The proposed method achieves a higher reconstruction quality, in terms of the peak signal-to-noise ratio (PSNR), than those achieved by the MAXSHIFT and GSB methods.

The remainder of the paper is organized as follows. Section II describes the proposed compression method. Section III presents the experimental results. The concluding remarks present in Section IV.

II. Proposed Compression Method

The proposed compression method is depicted in Fig. 1. First apply a 3D-IWT to an input 3-D medical image. This transform maps integers to integers and allows for perfect invertibility with finite precision arithmetic, which is required for perfect reconstruction of a signal [12]. The same wavelet filters are used in all three dimensions to perform separable wavelet decomposition. The 2-D spatial transform and temporal transform (along image slices) are done separately by first performing a 2-D dyadic wavelet decomposition on each image slice, and then performing a 1-D wavelet packet decomposition along the resulting image slices. Each level of decomposition, r, of the transform decomposes the 3-D image input into eight 3-D frequency sub-bands denoted as LLLr, LLHr, LHLr, LHHr, HLLr, HLHr, HHLr and HHHr. The approximation low-pass sub-band, LLL, is a coarser version of the original 3-D image, whereas the other sub-bands represent the details of the image.

The decomposition is iterated on the approximation low-pass sub-band. Its smooth (s) and detail (d) outputs for an index n are given in (1) and (2) respectively. Note that the smooth and the detail outputs are the results of the application of the high-pass and the low-pass filters respectively. At the first sight it seems that the rounding-off in this definition of s(n) discards some information. The IWT is thus reversible and its inverse is given in equations (3) and (4).

$$s(n) = [(x(2n) + x(2n+1))/2] \quad (1)$$

$$d(n) = x(2n) - x(2n+1) \quad (2)$$

$$x(2n) = s(n) + [(d(n)+1)/2] \quad (3)$$

$$x(2n+1) = s(n) - [d(n)/2] \quad (4)$$

Then the method groups the wavelet coefficients into 3-D groups and computes the mean energy of each group. Then encode each group of coefficients independently using a modified EBCOT with 3-D contexts to create a separate scalable layered bit-stream for each group. The coordinates of the VOI in the spatial domain, in conjunction with the information about the mean energy of the grouped coefficients, are then used in a weight assignment model to compute a weight for each group of coded wavelet coefficients. These weights are used to reorder the output bit- stream and create an optimized scalable layered bit-stream with VOI decoding capabilities and gradual increase in peripheral quality around the VOI. At the decoder side, the wavelet coefficients are obtained by applying the EBCOT decoder. Finally, an inverse 3D-IWT is applied to obtain the reconstructed 3-D image.

It is important to mention that the proposed method attains VOI decoding capabilities after the 3-D medical imaging data is coded. This is particularly advantageous in interactive telemedicine applications, where different clients may request different VOIs of the same compressed 3-D image stored on a central server. The server may then transmit different versions of the same compressed bit-stream by simply performing the bit-stream reordering procedure for each requested VOI, thus saving time in recoding the entire 3-D image for each client's request. Note that the bit-stream reordering procedure can take place before transmission since the decoder is capable of decoding any bit-stream regardless of the order it is transmitted (due to the fact that code-cubes are encoded independently). Alternatively, the bit-stream reordering procedure may also be performed at the client side once the image has been fully transmitted.

There are three key techniques in the proposed compression method. The first is the modified EBCOT. The second is the weight assignment model. The last is the creation of an optimized scalable layered bit-stream.

A. Modified EBCOT

EBCOT is an entropy coding algorithm for 2-D wavelet transformed images, which generates a bit-stream that is both resolution and quality scalable [9]. EBCOT partitions each sub-band in small group of samples, called code-blocks, and generates a separate scalable layered bit-stream for each code-block. The algorithm is based on context adaptive binary arithmetic coding and bit-plane coding, and employs four coding passes to code new information for a single sample in the current bit-plane. The coding passes are 1) zero coding (ZC), 2) run-length coding (RLC), 3) sign coding (SC), and 4) magnitude refinement (MR). A combination of the ZC and RLC passes encodes whether or not sample becomes significant in the current bit-plane. A sample is said to be significant in the current bit-plane if and only if $|C| \geq 2^p$. If sample C becomes significant in the current bit-plane, the SC pass encodes the sign information of sample. The MR pass encodes the value of sample C only if it is already significant in the current bit-plane p.

EBCOT encode the wavelet coefficients on a slice-by-slice basis. However, in our compression method, the input samples to the entropy coding algorithm are 3D-IWT wavelet coefficients rather than 2D-IWT wavelet coefficients. Therefore, coding 3D-IWT wavelet coefficients on a slice-by-slice basis makes EBCOT less efficient since the correlation between coefficients is not exploited in three dimensions. Consequently, a modified EBCOT algorithm is needed to overcome this problem, which solve by partitioning each 3-D sub-band into small 3-D groups of samples (i.e., wavelet coefficients), which is called as code-cubes, and coding each code-cube independently by using a modified EBCOT with 3-D contexts.

In this work, code-cubes are comprised of a×a×a samples and describe a specific region of the 3-D image at a specific decomposition level. In this approach, a code-cube of size a×a×a samples and position $\{x, y, z\}$ at decomposition level is related to a code-cube of size $a/2 \times a/2 \times a/2$ samples and position $\{x, y, z\}$ at decomposition level r+1, where r=1 is the first decomposition level. Fig. 2 shows the 3D-IWT sub-bands of a 3-D image after two levels of decomposition in all three dimensions with a single code-cube in sub-bands HHH2and HHH1. It is possible to access any region of the 3-D image at any resolution, which is essential for VOI coding. In this work, limit the code-cube dimension, a, to be a power of 2, with $a \geq 2^3$.

The proposed method encodes each code-cube independently using a modified EBCOT with 3-D contexts that exploit inter-slice correlations. Coding wavelet coefficients by extending

2-D context modeling to 3-D has been extensively used to improve coding efficiency [1], [2], [14], [15].

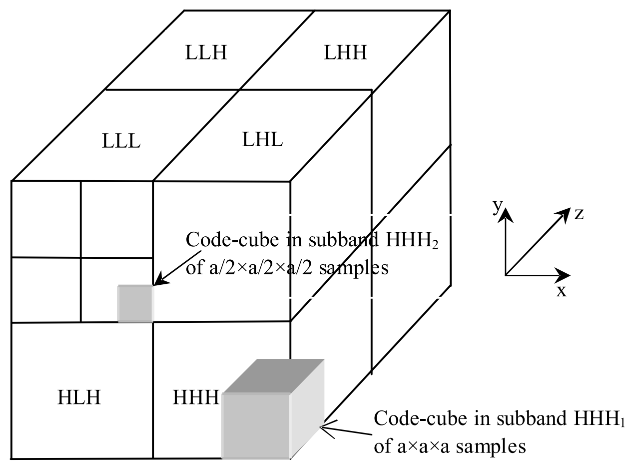

Fig. 2. 3D-IWT sub-bands of a 3-D image after two levels of decomposition in all three dimensions with a single code-cube in sub-bands HHH1 and HHH2

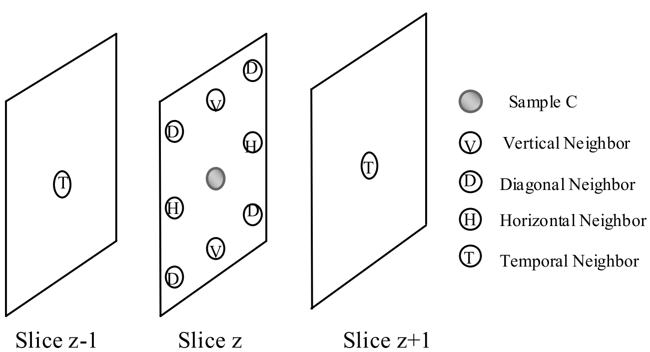

Fig. 3 The immediate horizontal, vertical, diagonal and temporal neighbors of sample C located in slices z, slices z-1 and z+1.

The method propose a 3-D context model, based on the four coding passes previously discussed, that incorporates information from the immediate horizontal, vertical, diagonal and temporal neighbors of sample located in slices z, z-1 and z+1, as illustrated in Fig. 3.

During the ZC pass, code whether or not sample c becomes significant in the current bit-plane p. The significance of sample c is highly dependent upon the value of its immediate horizontal, vertical and diagonal neighbors. Here, in order to exploit interslice correlations, it also employs the information about the significance of the immediate temporal neighbors to code the significance of sample c.

For the SC pass, we expect that the sign information of sample exhibit some correlation with that of its temporal neighbors, in addition to the correlation exhibited with its vertical and horizontal neighbors. Therefore, in this pass, it employs the sign and significance information of the temporal, vertical and horizontal neighbors to code the sign information of sample c.

For the MR pass, we also expect that the magnitude of sample c exhibit some correlation with the magnitude of its immediate temporal neighbors. We thus employ the significance information of the immediate temporal neighbors, in addition to the significance information of the immediate horizontal and vertical neighbors, to code the magnitude of sample c.

B. Weight Assignment Model

The purpose of the weight assignment model is to enable the encoder to reorder the output bit-stream, so that the code-cubes that constitute the VOI are included earlier while allowing for gradual increase in peripheral quality around the VOI, under the constraint that the VOI is the main focal point. In the proposed compression method, we apply this technique to decode contextual background information with peripherally increasing quality around the VOI, which in turn enhances the visualization of the data at any bit-rate. We achieve this by considering two main factors: 1) the proximity of a code-cube to the VOI and 2) the mean energy of a code-cube. The desired weight assignment for code-cube Cc_i is a function of the form

$$W_{Cc_i}(P_{Cc_i}, B_{Cc_i}, \rho_{Cc_i}) \in [0,1] \quad (5$$

where P_{Cc_i} is a value in the range [0,1] that depends on the proximity between the center of code-cube Cc_i and the center of the VOI, B_{Cc_i} is a value in the range [0,1] that depends on the mean energy of code-cube Cc_i, and ρ_{Cc_i} is a value in the range [0,1] that depends on the proportion of wavelet coefficients of code-cube Cc_i that contributes to the VOI.The main objective is to assign the largest weight to those code-cubes within the VOI, a smaller weight to those code-cubes within the non-empty background, and the smallest weight to those code-cubes within the empty background.

We employ $\rho_{Cc_i} \in [0,1]$as a measure of the proportion of wavelet coefficients of code-cube Cc_i that contribute to the VOI, withρ_{Cc_i} =0 for those code-cubes outside the VOI, $\rho_{Cc_i} = 1$ for those code-cubes that fully contribute to the VOI and $0 < \rho_{Cc_i} < 1$ for those code-cubes with some contribution to the VOI.

In order to determine which code-cubes constitute the empty background, we use the information about their mean energy, which for code-cube Cc_i is calculated as follows:

$$\hat{\mathcal{E}}_{Cc_i} = \frac{1}{K}\sum_{k=1}^{K} C_k^2 \quad (6)$$

where C_k is the kth sample of Cc_i, and K is the total number of samples in Cc_i . We expect the value of $\hat{\mathcal{E}}_{Cc_i}$ to be zero for those code-cubes within the empty background. The simplest possible method to determine if a codecube is part of the empty background is to use a thresholding approach, where Cc_i code-cube is considered to constitute the empty background if the mean energy $\hat{\mathcal{E}}_{Cc_i}$ is below a defined value. We, thus, use the following simple continuous, monotonically decreasing function to determine if code-cube Cc_i in sub-band is part of the empty background

$$B_{Cc_i} = 1 - \frac{\mathcal{E}_{Cc_i}}{\max_{Cc_i \in s}\{\mathcal{E}_{Cc_i}\}} \in [0,1] \quad (7)$$

where $\max_{Cc_i \in s}\{\hat{\mathcal{E}}_{Cc_i}\}$ is the maximum mean energy $\hat{\mathcal{E}}_{Cc_i}$ in subband. A value of B_{Cc_i} close to one means a high probability that code-cube Cc_i is part of the empty background, corresponding to a low mean energy content, whereas a value of B_{Cc_i} close to zero means a low probability that code-cube Cc_i is part of the empty background, corresponding to a high mean energy content. All values B_{Cc_i} are calculated during the encoding process and are stored as header information.

We now define function $W_{Cc_i}(P_{Cc_i}, B_{Cc_i}, \rho_{Cc_i})$ to assign weight W_{Cc_i} to code-cube Cc_i. We also employ a continuous, monotonically decreasing function with a range [0,1] as follows:

$$W_{Cc_i}(P_{Cc_i}, B_{Cc_i}, \rho_{Cc_i}) = \rho_{Cc_i} + (1 - \rho_{Cc_i})e^{-\left(\frac{B_{Cc_i}}{P_{Cc_i}}\right)^2} \quad (8)$$

where B_{Cc_i} is as defined in (7), ρ_{Cc_i} is the proportion of wavelet coefficients of code-cube Cc_i that contributes to the VOI, and P_{Cc_i} is the probability that code-cube Cc_i is located peripherally close to the VOI and is calculated by

$$P_{Cc_i} = 1 - \frac{d_{Cc_i}}{\sqrt{x^2+y^2+z^2}} \in [0,1] \quad (9)$$

where d_{Cc_i} is the radial distance between the center of the VOI and the center of the region represented by code-cube Cc_i in the spatial domain, and $\sqrt{x^2+y^2+z^2}$ is the maximum radial distance in the spatial domain between two samples of the 3-D image, where {x, y, z} denotes the size of the 3-D image in the spatial domain. A value of P_{Cc_i} close to one means a high probability that code-cube Cc_i is located peripherally close to the VOI; whereas a value of close to zero means a low probability that code-cube Cc_i is located peripherally close to the VOI.

Note that after the image is coded, the calculation of the code-cube weights for any VOI requires only the recomputation of two values for each code-cube, 1) its probability of being peripherally close to the VOI (i.e., value P_{Cc_i}), and 2) its contribution to the VOI (i.e., value ρ_{Cc_i}). There is no need to recompute the code-cube probabilities of being within the empty background (i.e., values B_{Cc_i}), since these probabilities are independent of the VOI and are calculated only once during the coding process (values B_{Cc_i} are stored as header information).

C. Creation of an Optimized Scalable Layered Bit-Stream

The bit-stream of each code-cube Cc_i may be independently truncated to any of a collection of different lengths, due to the entropy coding process, which is performed using a number of coding passes. We organize these truncated bit-streams into a number of quality layers to create a scalable layered bit-stream. This is done by collecting the incremental contributions from the various code-cubes into the quality layers such that the codecube contributions result in a rate-distortion optimal representation of the 3-D image, for each quality layer L. The code-cube incremental contributions into each quality layer are stored as header information during the coding process.

In this work, we employ the mean square error (MSE) to quantify the distortion of code-cube Cc_i at quality layer L

$$M^L_{Cc_i} = \frac{1}{K}\sum_{k=1}^{K}(c_k - \hat{c}_k)^2 \quad (10)$$

where c_k is the kth sample of Cc_i, $\hat{c}_k$ is the quantized representation of the kth sample of Cc_i associated with the truncated bit-stream at quality layer L, and K is the total number of samples in Cc_i.

The MSE of code-cube Cc_i at quality layer L in sub-band s on a per-voxel basis over the entire 3-D image may then be calculated as

$$\overline{M}^L_{Cc_i} = \frac{g_s}{N_s}\frac{q_s}{Q}M^L_{Cc_i} = 2^{2r}\frac{g_s}{N_s}M^L_{Cc_i} \quad (11)$$

where Q is the total number of image voxels, r is the decomposition level to which Cc_i belongs (r = 1corresponds to the first decomposition level), $q_s = Q/2^{2r}$ is the number of coefficients in s, N_s is the number of code-cubes in s (the code-cubes are of equal size), $M^L_{Cc_i}$ is as defined in (10), and factor g_s is a function of the specific wavelet filters used for reconstruction and is calculated from the filter coefficients [16].

In order to attain a gradual increase in peripheral quality around the VOI, we define a weighted MSE for code-cube Cc_i over the entire reconstructed 3-D image as follows:

$$\overline{\overline{M}}^L_{Cc_i} = \frac{1}{(1+W_{Cc_i})}\overline{M}^L_{Cc_i} \quad (12)$$

where W_{Cc_i} is the weight of Cc_i as defined in (4) and $\overline{M}^L_{Cc_i}$

is as defined in (11). Note that for code-cubes within the VOI, $W_{Cc_i} = 1$ and $\hat{\bar{M}}^L_{Cc_1} = (1/2)\bar{M}^L_{Cc_1}$ .However, for code-cubes outside the VOI, $W_{Cc_i} < 1$ and $\hat{\bar{M}}^L_{Cc_1} > (1/2)\bar{M}^L_{Cc_1}$.

The key to attaining VOI decoding capabilities at quality layer L, is to include only the truncated bit-streams of those code-cubes within the VOI. Under this condition, the output bit-stream at quality layer L is the summation of the truncated bit-streams of the code-cubes within the VOI

$$R_{Y^L} = \sum_{Cc_i \in VOI} R_{y^L_{Cc_i}} \quad (13)$$

where R_{Y^L} denotes the overall bit-rate of Y^L and $R_{y^L_{Cc_i}}$ denotes the bit-rate of $y^L_{Cc_i}$.

In order to increase the overall quality of the reconstructed 3-D image at quality layer L, while retaining the VOI decoding capabilities and allowing for the decoding of contextual background information, we encode some bit-streams $y^L_{Cc_i} \notin \text{VOI}$ along with bit-streams $y^L_{Cc_i} \in \text{VOI}$. Hence, the distortion can be expressed as follows:

$$D^L = \sum_{i=1}^{l} \hat{\bar{M}}^L_{Cc_i} \delta(y^L_{Cc_i}) + \sum_{i=1}^{l} \hat{\bar{m}}^L_{Cc_i} \delta(1 - y^L_{Cc_i})$$

$$= \sum_{i=1}^{l} \delta(y^L_{Cc_i}) \left[\hat{\bar{M}}^L_{Cc_i} - \hat{\bar{m}}^L_{Cc_i}\right] + \sum_{i=1}^{l} \hat{\bar{m}}^L_{Cc_i} \quad (14)$$

where $\hat{\bar{m}}^L_{Cc_i}$ denotes the weighted MSE added to the overall distortion D^L if $y^L_{Cc_i}$ is not included in layer L, and $\hat{\bar{M}}^L_{Cc_i}$ is as defined in (12). Using (10)–(12), $\hat{\bar{m}}^L_{Cc_i}$ is calculated by equating $\hat{c}$, the quantized representation of the kth sample of code-cube Cc_i , to zero. Where $\delta\ y^L_{Cc_i})$ (is 1 if $y^L_{Cc_i}$ is included in layer L (otherwise it is zero).

In order to attain the optimal overall reconstruction quality of the 3-D image at quality layer L, we minimize D^L in (14) under two bit-rate constraints

$$\sum_{i=1}^{l} R_{y^L_{Cc_i}} \delta(y^L_{Cc_i}) \le R_{Y^L}$$

$$\sum_{Cc_i \notin VOI} R_{y^L_{Cc_i}} \delta(y^L_{Cc_i}) < \sum_{Cc_i \in VOI} R_{y^L_{Cc_i}} \delta(y^L_{Cc_i}) \quad (15)$$

where $R_{y^L_{Cc_i}}$ is the bit-rate of $y^L_{Cc_i}$, R_{Y^L} is the maximum available bit-rate at quality layer L, and $\delta(y^L_{Cc_i})$ is 1 if $y^L_{Cc_i}$ is included in layer L (otherwise it is zero). Note that the constraints in (15) force the bit-rate spent on bit-streams $y^L_{Cc_i} \notin \text{VOI}$ to be less than the bit-rate spent on bit-streams $y^L_{Cc_i} \in \text{VOI}$. This guarantees that the VOI is decoded at higher quality than the rest of the 3-D image.

We solve the optimization problem defined in (14), (15) by finding the points that lie on the lower convex hull of the rate distortion plane corresponding to the possible sets of bit-stream assignments.

TABLE I. LOSSLESS COMPRESSION RATIOS AND BIT-RATES OF 3-D MEDICAL IMAGES USING VARIOUS COMPRESSION METHODS

Modality Size {x,y,z}(mm)	**Compression method**		
	MAXSHIFT method	***GSB method***	***Proposed method***
	Compression ratio (bit-rate, bits per voxel)		
1. MRI {240,240,10}	2.39:1 (3.34 bpv)	2.46:1 (3.25bpv)	2.44:1 (3.27 bpv)
2. MRI {256,256,20}	1.98:1 (4.04 bpv)	2.02:1 3.96 bpv)	2.00:1 (4.00 bpv)
3. MRI {272,272,100}	4.25:1 (1.88bpv)	4.31:1 (1.85 bpv)	3.34:1 (1.83 bpv)

MRI: Magnetic Resonance Imaging, bpv: Bits Per Voxel

III. Experimental Results

We compared the performance of the proposed compression method to that of 3D-JPEG2000 with VOI coding, using the MAXSHIFT and GSB methods. 3D-JPEG2000 employs a 3-D discrete wavelet transform across the slices with the resulting 3-D sub-bands being entropy coded by first grouping coefficients into smaller 3-D sections called 3-D code-blocks.

In our proposed compression method, we employed the Le Gall 5/3wavelet filter implemented using the lifting step scheme to decompose the test images with three levels of decomposition in all three dimensions. For the case of 3D-JPEG2000, we employed three levels of decomposition in all three dimensions.

Lossless compression ratios and bit-rates for the three evaluated methods are tabulated in Table I. The proposed method achieves compression ratios comparable to those achieved by MAXSHIFT and the GSB method, with the additional advantage of allowing for decoding any VOI from the same compressed bit-stream.

In order to measure the reconstruction quality of the VOI and background at different bit-rates, we employed the PSNR which for a 3-D image of bit-depth m is defined by

$$PSNR = 20 \log_{10} \frac{(2^m - 1)}{\sqrt{MSE}} \quad (17)$$

$$MSE = \frac{1}{K} \sum_{k=1}^{K} (c_k - \hat{c}_k)^2 \quad (18)$$

where MSE denotes the mean square error, $(2^m - 1)$ is the maximum voxel value in the 3-D image, K is the total number of voxels in the area to be evaluated (e.g., the VOI), c_k and are $\hat{c}_k$ the original and reconstructed values of the kth voxel, respectively.

It is important to remember that, in the proposed method, the entropy coding process needs to be performed only once for a 3-D medical image, since the decoding of a VOI simply requires the reordering of the compressed bit-stream. Finally, it is important to remark that in the proposed method, all information needed to perform the bit-stream reordering procedure and layer optimization technique is stored and transmitted as header information.

IV. Conclusion

We presented a scalable 3-D medical image compression method with optimized Volume of Interest coding within the framework of interactive telemedicine applications. The method is based on a 3-D integer wavelet transform and a modified version of EBCOT that exploits correlations between wavelet coefficients in three dimensions and generates a scalable layered bit-stream. The method employs a bit-stream reordering procedure and an optimization technique to optimally encode any VOI at the highest quality possible in conjunction with contextual background information from a lossy to a lossless representation. We demonstrated the two main novelties of the method; namely, the ability to decode any VOI from the compressed bit-stream without the need to recode the entire 3-D image; and the ability to enhance the visualization of the data at any bit-rate by including contextual background information with peripherally increasing quality around the VOI. The proposed method will achieves higher reconstruction qualities than those achieved by 3D-JPEG2000 with VOI coding at a variety of bit-rates.

References

[1] P. Schelkens, A. Munteanu, J. Barbarien, M. Galca, X. Giro-Nieto, and J. Cornelis, "Wavelet coding of volumetric medical datasets," *IEEE Trans. Med. Imag.,* vol. 22, no. 3, pp. 441–458, Mar. 2003.

[2] Z. Xiong, X.Wu, S. Cheng, and J. Hua, "Lossy-to-lossless compression of medical volumetric images using three-dimensional integer wavelet transforms," *IEEE Trans. Med. Imag.,* vol. 22, no. 3, pp. 459–470, Mar. 2003.

[3] R. Srikanth and A. G. Ramakrishnan, "Contextual encoding in uniform and adaptive mesh-based lossless compression of MR images," *IEEE Trans. Med. Imag.,* vol. 24, no. 9, pp. 1199–1206, Sep. 2005.

[4] J. M. Shapiro, "Embedded image coding using zerotrees of wavelet coefficients," *IEEE Trans. Signal Process.,* vol. 41, no. 12, pp. 3445–3462, Dec. 1993.

[5] A. Said and W. Pearlman, "A new fast and efficient image coded based on set partitioning in hierarchical trees," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 6, no. 3, pp. 243–250, Jun. 1996.

[6] D. Taubman, "High performance scalable image compression with EBCOT," *IEEE Trans. Image Process.*, vol. 9, no. 7, pp. 1158–1170, Jul. 2000.

[7] K. Krishnan. M. Marcellin, A. Bilgin, and M. Nadar, "Efficient transmission of compressed data for remote volume visualization," *IEEE Trans. Med. Imag.,* vol. 25, no. 9, pp. 1189–1199, Sep. 2006.

[8] Y. Liu and W. A. Pearlman, "Region of interest access with three dimensional SBHP algorithm," in *Proc. SPIE,* 2006, vol. 6077, pp. 17–19.

[9] C. Doukas and I. Maglogiannis, "Region of interest coding techniques for medical image compression," *IEEE Eng. Med. Biol. Mag.,* vol. 25, no. 5, pp. 29–35, Sep.–Oct. 2007.

[10] I. Ueno and W. Pearlman, "Region of interest coding in volumetric images with shape-adaptive wavelet transform," in *Proc. SPIE,* 2003, vol. 5022, pp. 1048–1055.

[11] JPEG 2000 Part I: Final Draft International Standard (ISO/IEC FDIS15444-1), ISO/IECJTC1/SC29/WG1 N1855, Aug. 2000.

[12] A. R. Calderbank, I. Daubechies, W. Sweldens, and B. L. Yeo, "Wavelet transforms that map integers to integers," Appl. Comput. Harmon. Anal., vol. 5, no. 3, pp. 332–369, 1998.

[13] I. Daubechies and W. Sweldens, "Factoring wavelet transform into lifting steps," *J. Fourier Anal. Appl.,* vol. 41, no. 3, pp. 247–269, 1998.

[14] J. Xu, "Three-dimensional embedded subband coding with optimized truncation (3-D ESCOT)," *Appl. Computat. Harmonic Anal.,* vol. 10, pp. 290–315, 2001.

[15] N. Zhang, M. Wu, S. Forchhammer, and X. Wu, "Joint compression segmentation of functional MRI data sets," in *Proc. SPIE*, 2003, vol. 5748, pp. 190–201.

[16] B. Usevitch, "Optimal bit allocation for biorthogonal wavelet coding," in Proc. Data Compression Conf., Snowbird, UT, Mar. 1996, pp. 387–395, 1996.