ROI Based Encoding of Medical Images: An Effective Scheme Using Lifting Wavelets and SPIHT for Telemedicine

T. M. P. Rajkumar and Mrityunjaya V Latte

***Abstract*—Telemedicine characterized by transmission of medical data and images between users is one of the emerging fields in medicine. Huge bandwidth is necessary for transmitting medical images over the internet. Resolution factor and number of images per diagnosis makes even the size of the images that belongs to a single patient to be very large in size. So there is an immense need for efficient compression techniques for use in compressing these medical images. Each of the regions that are considered to be more important than others in medical images is termed as a Region of Interest (ROI) e.g. tumor region of the brain MRI. Thus, the regions of interest can be coded with high spatial resolution than the background while transmitting the images. By this, ROI of high compression rate and high quality can be obtained. This paper reviews the application of ROI coding in the field of telemedicine. Wavelet transform with lifting is used to perform image coding based on Set Partitioning in Hierarchical Trees (SPIHT). ROI coding with high spatial resolution than the background is accomplished using tiling method. High compression ratio is achieved by obtaining the ROI through user interaction and coding with the user given resolution. The experimental result shows that the application of ROI coding achieves high compression rate and quality ROI by using wavelet with lifting and tiling method**

***Index Terms*—Image compression, Telemedicine, Region of Interest (ROI), Tiling, Wavelet transform, Lifting, SPIHT.**

I. INTRODUCTION

Medical field is an enormous domain which is becoming transformed with the development of science and technologies. A collaboration of telecommunication technology with clinical medicine called telemedicine is one of the branches of medical field which is considered to be a developing technology. Telemedicine is important in medical diagnosis, treatment, and patient care. Real-time mode and store-and-forward are the two modes in which it is operated.. In the real-time mode, it is immediately made available at the remote terminal after the patient's data is acquired. But, the store-and-forward mode stores as well as access the data in due course [1]. Here, any medical image can be the data. Images or other types of digital signals are used to express a majority of the modern medical data including MRI, computer Tomography (CT), Ultrasound, and Positron Emission Tomography (PET) [24].

The diagnostic and therapeutic strategies require images [6]. Among several users the images have to be shared. Images of high resolution and size are obtained with improved modern digital cameras [2]. High memory space is occupied by medical images because of the resolution factor. Image compression is used to avoid this problem. A significant role in archiving and transmission of medical images is played by Image compression [19].

Data compression is the other name for Image compression. A data stream of smaller dimension than the input data stream is obtained by the image compression process. The data compression technology has grown rapidly in the last two decades [4]. Several transforms like DCT, DFT etc., can be used to accomplish image transformations [25] A topic of interest for better compression has been the Contourlet based ROI with wavelet transform of digital signals and images. By using computationally costly extensive processing data compression has relieved the burden of image transmission and storage [23]. Data compression tries to reduce the size of the image by focusing on the removal of redundant data. Storage area of the image is doubled by compressing an image into half its original size [5]. In other words, image compression by removing the spatial and spectral redundancies considerably reduces the number of bits required to represent an image [26]. This facilitates considerable reduction in the bandwidth requirement for transmitting an image over the internet. Data storage, archiving and transmission of medical images over the internet to the end user have significant applications for data compression [6].

Image compression may lead to loss of relevant medical information though it is an important aspect for improving the transmission speed and storage [20]. The fact that the neighboring pixels of most images are highly correlated and have common characteristics is exploited by image compression [21]. Based on the information content of the newly constructed image compression are of two types; they are lossless and lossy [6]. Lossless algorithms such as JPEG (2000) and wavelet-based compression appears to have gained a substantial footing in several applications though lossy compression methods are rarely for clinical purposes [6]. Image compression makes extensively use wavelet transform. At high compression ratios, the quality of a picture is improved by a wavelet. Several schemes based on wavelet have been developed and employed for data compression during the last decade. Of these, JPEG (2000) is considered as a standard for compression of still images [5]. The accurate diagnostic results are extracted by these compression methods without any loss or error. However the clinical diagnostic decision will be affected by any loss or error in the data compression. The obtained data is highly

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complex and is required to be error-free. So obtaining precise results necessitates maintaining an immense perfection [3].

All regions of medical images and certain real time images do not have equal importance. Special consideration is given only to a few item(s) of the image [28]. For instance the section of image that contains the tumor is examined for instead scanning the whole image in medical images such as the brain MRI Region of interests (ROI) are the regions that are considered to be important in any given image [27. ROI of the image i.e., patient information and image parameters will be of greater significance and hence they will be coded with high spatial resolution than the background while transmitting an image. Therefore, compared to compression of the entire image, high reconstruction quality over user specified spatial regions in a limited time can be obtained by ROI coding. In addition, a good trade-off between image quality and compression ratio is provided by ROI coding [22]. Consequently, compared to the background, a higher quality or spatial resolution than the background is obtained by decoding the ROI [7]. In a photographic image, people often wish to look into the faces of the people. The regions of an image that contain faces can be coded as ROI's by using automated face detection algorithm and eventually stored with more precision than the non-face sub-images Client/server application for image browsing utilizes this. In wavelet based compression, ROI coding can be developed [29]. Tiling, code block selection, and coefficient scaling are three mechanisms available to encode and decode the images with varying spatial detail. In the tiling approach, an image file is the fundamental part encoded in wavelet compression [30].

An image can be coded either as a single tile or by separately coding each tile obtained by partitioning the image into non-overlapping sub images. The local memory required to perform the discrete wavelet transform (DWT) can be reduced by using the tiling method. Using tiling method, spatially unique regions of the images can be accessed and coded with variable quality as needed [7]. Parsing of a wavelet bit-stream and extraction of the packets that has the necessary code-blocks for decoding the ROI [Code-block selection are involved in the code block selection process [31]. While coding, the background is made less significant than ROI using coefficient scaling also known as max shift algorithm which shifts all the background coefficients less than one. However coding efficiency is reduced by coefficient scaling.

This paper presents the application of ROI coding in the field of telemedicine. First, the ROIs and their respective resolutions must be specified by the user. After this, the input image is partitioned and the ROI are extracted from each of the tiles using the tiling method. The extracted tiles belong to various ROI(s) and their residual background. SPIHT encoding is performed after transforming each and every tile using lifting wavelet. Then the final ROI encoded image data is obtained by integrating the SPIHT encoded tiles into a single unit. By integrating the encoded ROI image data appropriately the background is made to come after the ROI tiles which appear first in the encoded image data. This encoded image block is appended with a header that consists of information related to the number of ROIs, co-ordinates and resolutions of each ROI. The ROI then reconstructs the image such that the background tile is decoded only after decoding the ROI. The resolution available in the header of the encoded data is used to decode the tiles. The ROI tiles are displayed in the corresponding co-ordinates after the decoding phase using the co-ordinate details.

The rest of the paper is organized as follows: Section II presents a brief review of the related literature and a detailed overview of the wavelet transform is given in Section III. Section IV discusses the proposed ROI coding scheme for medical images and the experimental results are presented in Section V. Finally, the conclusions are summed up in Section VI.

II. Review of Related Research

A handful of researches are available in the literature for encoding an image based on ROI. Recently, utilization of wavelets and techniques like SPIHT and AT-SPIHT for encoding of ROI has received a great deal of attention among the researchers. A brief review of some of the recent research works is presented here.

Singara Singh *et al*. [10] have presented a method to compress the graphics images after distinguishing the real color images from the graphics images with improved compression performance by using a wavelet transform extension under JPEG2000 standard. Without altering the syntax of compressed stream of JPEG2000, their method could be employed with ease in image compression applications.

E. Logashanmugam and R. Ramachandran [11] have concentrated on the application of new sub-band coding algorithm of wavelet transform on image compression. Also they have achieved wavelet-based compression of natural image using a visually lossy contrast-based quantization algorithm. They have examined the compression ratio by employing the DWT to numerous images. The performance of their method has been proved to be good by evaluating their method with the existing compression technique.

K. Veeraswamy and S. SrinivasKumar [14] have proposed a method to improve the performance of wavelet-based image compression under conditions of entropy. Based on the sub-band energy, the entire sub-bands of wavelet decomposed image have been quantized. In a predestined manner, they have re-arranged the quantized and rounded coefficients in the LL sub band. They have lowered the entropy (bits/pixel), by employing a prediction algorithm. In addition, using a compressed LL sub band, they have introduced an oblivious image watermarking algorithm. They have calibrated the performance of the watermarking algorithm on the basis of Peak Signal to Noise Ratio (PSNR) and Normalized Cross Correlation (NCC). Also, their algorithm has been robust to several attacks on watermarked images, such as JPEG and JPEG2000 compression.

Nan Zhang *et al*. [16] have presented an efficient two-description image coding method. The two side descriptions of an image have been produced by the quincunx sub sampling. An interpolation process with sample correlation has been used to perform the decoding from any side of the description. Since the pixels are not lined rectilinearly, each side description was not agreeable to the existing image coding techniques, although the quincunx sub sampling was an automatic option for the most excellent use of sample correlations in image multiple-description coding (MDC). They have demonstrated the way in which adaptive directional lifting (ADL) transform which is generally appropriate for decorrelating samples on the quincunx lattice can be used to subdue this problem. A practical MD image encoder could be constructed by rooting the ADL transform into the JPEG 2000. They have proved that better coding performance could be achieved by their image MDC scheme by experimental results.

D. Vijendra Babu and N.R. Aflame [17] have utilized Partial EZW Algorithm in the Enhanced Image Compression Method, they have proposed. They have used progressive Shapiro's Embedded Zero tree Wavelet (EZW) algorithm as the basis for their approach. The complexity of EZW that looses its potential in transmitting lower bit planes has been overcome in their Partial EZW Algorithm. By adding integer wavelet transformation and ROI coding, the Partial EZW has been made better than EZW and SPIHT Algorithm and results have proved this.

Kamrul Hasan Talukder and Koichi Harada [18] have analyzed and assessed the concurrency in communicating threads that accomplish the wavelet transformation concurrently. The communication among threads is obtained by framing the grammar and its syntax. Furthermore, they have properly established the system molded in Symbolic Model Verifier (SMV).

Emmanuel Christophe and William A. Pearlman [8] have proposed an image compression algorithm expansion called 3D-SPIHT (Set Partitioning In Hierarchical Trees). Random access decoding of a specific spatial resolution and particular bit rate from a single code stream has been facilitated by their algorithm. They have separately performed the selections of the final spatial and spectral (or axial) resolutions. They have performed the encoding of the image wavelet transform in tree blocks. They have utilized a rate-distortion optimization procedure to lower the bit rates of these tree blocks. While reading a least number of bits from the coded data, a heterogeneous resolutions and characteristics of the images could be extracted. In contrast to the JPEG2000 Multi-component algorithm, the characteristics and competence of 3D-SPIHT expansion has been confirmed for a range of medical and hyper spectral images.

T. K esavamurthy *et al.* [9] have proposed AT-SPIHT algorithm based volumetric color medical image compression for the Picture Archiving and Communication Systems (PACS). Doctors have been enabled to employ the PACS in a better way for diagnosis and management in a short duration because by combining the RIS, HIS and the entire imaging modalities and scanning devices to it, it has stuck to the medical information system. Also in telemedicine applications, it has a probable manipulation. By the use of this technology, enormous digital images are generated and accumulated in PACS where volumetric color medical image compression has been crucial to use the PACS competently for the doctor's diagnostic use. Generally, the volumetric color medical images can be considered as a series of two- dimensional (2-D) slices which are fundamentally a three-dimensional (3-D) image data set. AT-SPIHT has been a competent advanced coding method operated on the 3-D color Computed Tomography (CT) medical image. In medical information system, the implementation and operation of PACS has been enabled by the more proficient spatial orientation tree structure employed by the AT-SPIHT algorithm.

Muna F. Al- Sammraie and Faisal G. Khamis [12] have presented a compression scheme through context-based spatial entropy coders based on adaptive Space-Frequency Segmentation decomposition method. The lossy coding for natural images utilizes content-based entropy techniques and in addition spatial encoding has been combined with their proposed compression scheme for adaptive wavelet coding. Results have demonstrated that a better image quality in comparison with other compression rates, has been provided by their proposed technique.

Enrique Guzman *et al.* [13] have presented a morphological associative memories based method for image compression. At the transforming stage of image encoding they have employed a new image transform that utilize MAM, thus changing old methods such as discrete cosine transform or discrete wavelet transform. Auto associative and hetero associative MAMs can be considered as a subclass of morphological neural networks. Hetero associative MAMs which are obtained from image sub blocks are generated by the Morphological Transform (MT). Utilizing a transformation matrix as an input pattern the MT has been operated in separate blocks of the image. Data compression has been performed at the following stages by employing the morphological representation obtained based on this matrix. Though MT has competent compression rate and signal-to-noise ratio compared to traditional transforms, the processing speed has been the major advantage provided by the MT in comparison with the earlier methods.

Li-bao Zhang and Xian-chuan Yu [15] have proposed a technique for medical image compression called general layered bit plane shift (GLBShift). The adaptability provided by their method for adjustment of the degree-of-interest of the ROI has been much more than that provided by the Max shift method. Also, the computational complexities of their method have been less than that of the general scaling based method provided by JPEG2000. The capability of their proposed method to provide considerably better visual quality for CT and MRI images at low bit rates has been proved by experimental results.

III. WAVELET TRANSFORM

Wavelet transforms have emerged as one of the most significant and potent tool for signal representation. Currently, image processing, data compression, and signal processing utilize wavelet transforms. A 'small wave' is indicated by the word wavelet. French seismologist Jean Morlet [32] introduced it as a theoretical formalism in 1980. The wavelet transform can be any selected function; it is more adaptable and can be shifted and dilated to examine signals. Wavelets can be inferred as small waves conceptually stated in a zero mean value. Wavelet transform obtains a two dimensional function of a and b by mapping a time function. The parameter a termed as scale compresses or stretches a function by scaling. The parameter b is termed as the translation of the wavelet function along the time axis.

Continuous Wavelet Transform and Discrete Wavelet Transform are two broad categories of the wavelet theory. Continuous Wavelet Transform (CWT) is utilized to separate a continuous-time function into wavelets. Unlike Fourier transform, continuous wavelet transform can create a time-frequency representation of a signal that provides excellent time and frequency localization. Continuous Wavelet Transform is a convolution of the input data series with a collection of functions produced by the mother wavelet. Any wavelet transform for which the wavelets are disjointedly sampled is called as a Discrete Wavelet Transform (DWT) [33]. Data compression is one use of the wavelet approximation. Effective compression can be achieved by encoding the data that is transformed by employing wavelet transform, like certain other transforms.

IV. Proposed ROI Encoding Scheme for Medical Images

One of the most significant features offered by JPEG-2000 is ROI coding. Instead of encoding the entire image as a single entity, it permits imposing heterogeneous fidelity constraints to diverse regions of the image. This property is particularly beneficial for image coding applications used for compressing medical images where the image is composed of regions that requires to be encoded at diverse bit rates. Important diagnostic information of most of the medical images is localized over reasonably small regions of interest. In this case, better utilization of the available bit rate can be achieved by employing region-based coding, because high quality is necessary only for the aforesaid diagnostically important regions and a lower bit rate encoding is sufficient for the remaining regions of the image. After efficiently selecting the ROI, by means of Cohen-Daubechies-Feauveau wavelet 9/7, first the significant region and the diagnostically insignificant region are transformed. Then, by means of SPIHT, the significant region and the diagnostically insignificant region are encoded with distinct resolutions. Some fundamental advantages of the proposed ROI-based coding scheme are as follows,

- ROI or ROIs can be of any standard rectangular shape.
- Visually annoying edges around the ROI are avoided by degrading the quality of the surroundings elegantly after ensuring the quality of the ROI.
- Different resolutions can be used for encoding multiple ROIs.

A. ROI-Based Encoder

The proposed ROI-based coding scheme involves the following steps,

1) User interaction mode of selection of ROI and their related resolution.
2) Extraction of user selected ROIs and residual background by means of the tiling process.
3) Lifting Wavelet Transform (LWT) employed decomposition of residual background and extracted ROIs.
4) Encoding the transformed image blocks by employing SPIHT
5) Ordering the encoded data segments to achieve effective image transmission.

Fig.1 illustrates the block diagram of the proposed ROI encoding scheme.

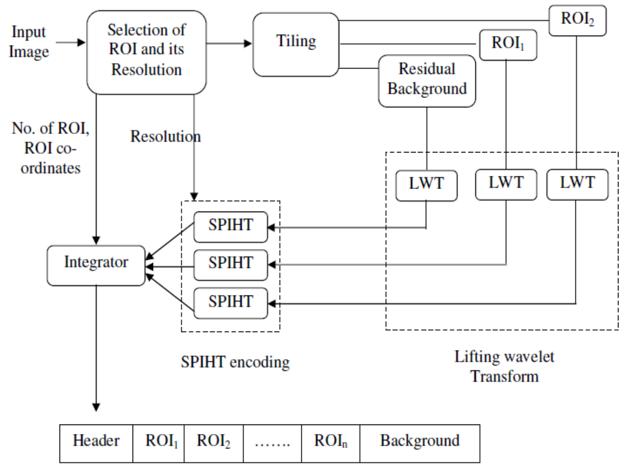

Fig. 1. Block diagram of the proposed ROI encoding scheme

1) ROI Selection with Resolution

Selecting ROI based on user interaction is the first step of the proposed ROI-based encoder. In medical imaging, it is obvious that all parts of the image are not important for diagnosis. Hence, identification of the significant parts of the images by the user is necessary. The user selects the ROIs from the image and gives them as well as their preferred resolution as input.

2) Tiling

Tiling can be described as the method of separating the image into several non overlapping blocks called tiles. Encoding is performed on the entire image by either considering it as a single tile or as several separate rectangular tiles. Regions Of Interest (ROIs) are extracted from the image (I), by the proposed scheme as a tile(s). In the original image, the pixel intensity values that correspond to the ROI are given a zero value as implied by the extraction. The pixels which form ROI(s) of the image are used to create the tile(s). Thus, a set of tiles will be created that correspond to each ROI and the residual background image having zero intensity values in the ROI. The entire available image blocks including the residual background image are regarded as tiles. These tiles are to be encoded separately with distinct resolution value.

3) Lifting Wavelet Transform

The Discrete Wavelet Transform (DWT) is an all-purpose signal processing tool that is employable in several engineering and scientific applications. DWT has been adopted in the forthcoming JPEG2000 image compression standard because it is especially successful in the area of image compression. Recently, the concept of lifting has facilitated improvement of power and versatility of the wavelet transforms by providing net insight and ideas on wavelets. Up to 100% higher than the computational efficiency of the common direct convolution based implementation is achieved by the efficient way of DWT implementation provided by lifting. The diverse tiles obtained from tiling can be regarded as signals. Lifting wavelet transform is employed for each signal. A given signal f_j is transformed into a coarser signal f_{j-1} and a detail signal d_{j-1} by wavelet transform with lifting. Fig.2 depicts this step of lifting wavelet transform. The following three processes are involved in the lifting scheme wavelet transform,

1) Split
2) Predict
3) Update

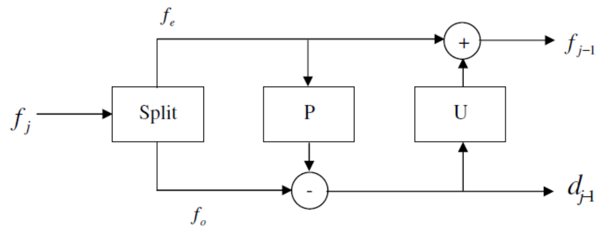

Fig. 2. A typical step of the lifting wavelet transform

Split

The given signal f_j can be partitioned into even f_e and odd f_o samples by applying a lazy wavelet.

Predict

Odd samples can be calculated if the even samples are specified because of the high correlation between neighboring samples of the signal. The average of the two even samples ($f_{j,2l}$, $f_{j,2l+2}$) adjacent to the odd sample $f_{j,2l+1}$ is calculated as the predicted value of the odd sample. The extent to which the given signal deviates from linearity can be measured as the difference between the predicted and original signal values of the odd sample. The thus obtained difference is the high frequency component of the signal.

$$d_{j-1,l} = f_{j,2l+1} - \frac{f_{j,2l} + f_{j,2l+2}}{2} \qquad (1)$$

Update

All the stages of decomposition should preserve the average of the signal.

$$\sum_l f_{j-1,l} = 1/2 \sum_l f_{j,l} \qquad (2)$$

By updating the even samples using the already computed detail coefficients $d_{j-1,l}$, a consistent average is maintained in the coarse signal.

$$f_{j-1,l} = f_{j-1,2l} + \frac{d_{j-1,l-1} + d_{j-1,l}}{4} \qquad (3)$$

Fig.3, illustrates one step of the wavelet transform with lifting. The required wavelet transform is obtained by continuing the process for the even sample of each step. The even and odd samples from the coarser and detail signal are computed to perform the inverse transform as depicted in fig. 3.

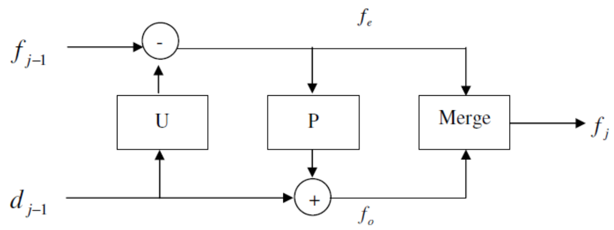

Fig. 3. A typical step of the inverse lifting wavelet transforms

$$f_{j,2l} = f_{j-1,l-1} - \frac{d_{j-1,l-1} + d_{j-1,l}}{4} \qquad (4)$$

$$f_{j,2l+1} = d_{j-1,l} - \frac{f_{j,2l} + f_{j,2l+2}}{2} \qquad (5)$$

where $f_{j,2l}$ and $f_{j,2l+1}$ are the even and odd samples of the reconstructed original signal, respectively. Thus the original signal can be obtained by combining these two samples.

4) SPIHT Encoding

SPIHT is used to individually encode the wavelet transformed tiles. Fig. 3 shows a typical transformed image. The transformed image is sent to the SPIHT encoder in such a sequence that will make the decoder to decode the most important details (ROIs) first and followed by the less important details. Most significant bits of significant coefficients that contain the significant information for reconstructing the image are sent first by the process. As we have to sort the spatially ordered coefficients to send the significant coefficients first, the information concerning their position must also be provided. The ordering data is not explicitly encoded with coefficients by SPIHT to overcome these problems. Instead, if the magnitude comparison results are given, the same execution path is obtained is followed by the encoding and decoding algorithm to obtain the ordering information.

SPIHT is one of the most superior methods available that surpasses even the modern JPEG 2000 under certain circumstances. The relationships among the wavelet coefficients across the diverse scales at the same spatial position in the wavelet sub bands are exploited by the set-partitioning in hierarchical trees (SPIHT) [35]. Normally, the coding of both the location of significant wavelet coefficients as well as the location of zero trees in the wavelet sub bands, are involved in SPIHT coding. Generally, the low frequency components contain most of the energy that exists in an image. As a result of this, the variance is reduced as we move from the highest to the lowest levels of the pyramid of the sub-bands. In addition to this, a spatial self-similarity exists between sub bands, and the coefficients are likely to be better magnitude-ordered as we move towards the lower sub-bands. For example, huge low-activity regions are likely to be recognized in the highest levels of the pyramid, which are subsequently duplicated at identical spatial locations in the lower levels.

The spatial relationship on the hierarchical pyramid is normally defined in a tree structure, called spatial orientation tree. The Fig. 4 shows the construction of a spatial orientation tree is defined in a pyramid with recursive four-sub band splitting. The pixel coordinate is used identify each node of the tree, where each node is represented by a pixel in the pixel coordinate. The pixels of the same spatial orientation in the next finer level of the pyramid correspond to their direct descendants (offspring). Always a group of 2 x 2 neighboring pixels is formed because the tree is defined in such a way that each node has either no offspring (the leaves) or four offspring. In Fig. 4, the arrows are tilting from the parent node towards its four offspring. The tree roots are represented by pixels in the highest level of the pyramid and are also grouped in 2 x 2 adjacent pixels. Nevertheless, they have different offspring branching rules, and one of them (indicated by the star in Fig. 4) in each group, has no descendants.

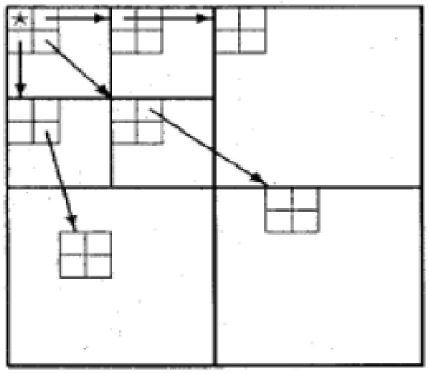

Fig. 4. Branching rule of the coding method

The coding method is presented using the following sets of coordinates

(i, j) is the pixel location that define a tree node and $O(i, j)$ is the set of its offsprings.

$D(i, j)$ is the set of descendants of node (i, j) .

$L(i, j)$ is a set obtained using the relation $L(i, j) = D(i, j) - O(i, j)$.

For all pyramid levels other than the highest and lowest, the set partitioning trees has,

$$O(i, j) = \{(2i,2j),(2i,2j+1),(2i+1,2j),(2i+1,2j+1)\} \quad (6)$$

The following rules are used to split a set (e.g. if it is significant),

1) For all $(i, j) \in H$ initial partition $D(i, j)$ is created with sets $(i; j)$.
2) $L(i, j)$ and four single-element sets with $(k,l) \in O(i, j)$ are obtained by partitioning $D(i, j)$ if it is significant.
3) Four sets $D(k,l)$ with $(k,l) \in O(i, j)$ are obtained by partitioning $L(i, j)$, if it is significant.

Coding algorithm

The three ordered lists used to accumulate the significance values of the wavelet coefficients modeled in the spatial orientation tree are as follows,

1) LIS, List of Insignificant Sets: consists of sets of wavelet coefficients which are defined by tree structures that have magnitude smaller than a threshold (are insignificant). The sets prohibit the coefficient belonging to the tree or all sub-tree roots, and have minimum four elements.
2) LIP, List of Insignificant Pixels: consists of individual coefficients that have magnitude lower than the threshold.
3) LSP, List of Significant Pixels: pixels that have magnitude greater than the threshold (are significant).
4) LIS entries will be either sets of the type $D(i, j)$ (type A) or sets of type $L(i, j)$ (type B)

During the sorting pass the pixels in the LIP are examined and those pixels which were insignificant in the previous pass but significant now are moved to the LSP. Afterwards, the sets in the LIS are assessed one after the other in the order in which it exists and once a significant set is found significant it is removed from the list and partitioned. The new sets are added again to the LIS if it has more than one element, otherwise it is added either at the end of the LIP or LIS depending on its significance. The significance function can be represented as,

$$S_n(T) = \begin{cases} 1, & \max\limits_{(i,j)\in T} \{|c_{i,j}|\} \geq 2^n, \\ 0, & otherwise \end{cases} \quad (7)$$

Algorithm

1) Initialization: output $n = \lfloor \log_2' (\max_{(i,j)}\{|c_{i,j}|\}) \rfloor$;

Set the LSP as an empty list, and add the coordinates $(i, j) \in H$ to the LIP, and only those with descendants also to the LIS, as type A entries.

2) Sorting Pass:

2.1) *for each entry (i, j) in the LIP do :*

 2.1.1) *output* $S_n(i, j)$;

 2.1.2) *if* $S_n(i, j) = 1$ *then move (i, j) to the LSP and output the sign of* $c_{i,j}$;

2.2) *for each entry (i, j) in this LIS do :*

 2.2.1) *if the entry is of type A then*

- *output* $S_n(D(i, j))$;
- *if* $S_n(D(i, j)) = 1$ *then*

 for each $(k,l) \in O(i, j)$ *do :*

- *output* $S_n(k,l)$;
- *if* $S_n(k,l) = 1$ *then add (k,l) to the LSP and output the sign of* $c_{k,l}$;
- *if* $S_n(k,l) = 0$ *then add (k,l) to the end of LIP;*

 if $L(i, j) \neq 0$ *then move (i, j) to the end of the LIS, as an entry of type B, and go to Step 2.2.2); otherwise, remove entry (i, j) from the LIS;*

 2.2.2) *if the entry is of type B then*

- *output* $S_n(L(i, j))$;
- *if* $S_n(L(i, j)) = 1$ *then*

 add each $(k,l) \in O(i, j)$ *to the end of the LIS as an entry of type A;*

 remove (i, j) from the LIS.

3) Refinement Pass: for each entry (i, j) in the LSP, expect those included in the last sorting pass (i.e., with same n),

output the n^{th} most significant bit of $|c_{i,j}|$;

4) Quantization-Step Update: decrement n by 1 and go to Step 2.

Some of the advantages of SPIHT encoding include: (i) allows a variable bit rate and rate distortion control as well as progressive transmission [34] (ii) an intensive progressive capability – we can interrupt the decoding (or coding) at any time and a result of maximum possible detail can be reconstructed with one-bit precision. (iii) Very compact output bit stream with large bit variability – no additional entropy coding or scrambling has to be applied.

A few benefits of SPIHT encoding include: (i) a variable bit rate and rate distortion control in addition to advanced transmission are permitted [34] (ii) an comprehensive progressive potential – we can suspend the decoding (or coding) at any time and a one-bit precision result of highest possible detail can be reconstructed (iii) Extremely concise output bit stream with substantial bit variability – application of extra entropy coding or scrambling is not required.

Each significant coefficient is identified by continuing the set partitioning process until the significance test is carried out on all single coordinate significant subsets. The new partitions are created such that insignificant subsets are made to contain several elements whereas significant subsets are made to have only one element. The significant bits of the significant coefficient of the current cycle are sent to the decoder during each cycle. The coding process is iterated for the suitable number of cycles to obtain the required resolution.

5) Organization of Encoded Data

The SPIHT encoded tiles are incorporated into a single block which consists of the ROI encoded image data. Tiles representing ROI are made to come first in the block i.e., before the background by sorting the encoded image data appropriately. To each block a header consisting of the following details are added.

1) Number of ROI
2) Co-ordinates of each ROI
3) Resolution of each ROI

Fig. 5 shows the format of the encoded image data.

Header	$EROI_1$	$EROI_2$	. . .	$EROI_n$	EBackground

Fig. 5. Format of the Final Encoded Data

B. ROI-Based Decoder

The decoding process is nothing but the reverse of the encoding process. First, all the ROI are sequentially decoded by the decoder which decodes the residual background (or non-ROI) at the end. Each tile is decoded by the decoder with the resolution specified in the header of the encoded image data. Using the co-ordinate details given in the header they are displayed in its corresponding position in the image, once the ROI tiles are decoded. Hence diverse tiles in the image will have diverse resolution in the displayed image. Fig. 6 shows the block diagram of the proposed ROI-based decoder.

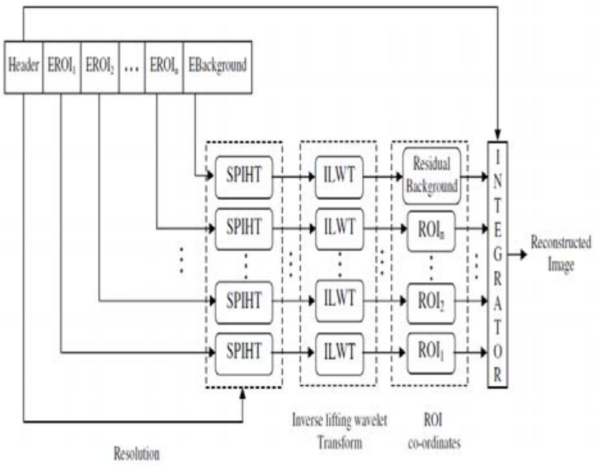

Fig. 6. Block diagram of the proposed ROI-based decoding scheme

V. Experimental Results

The proposed ROI coding scheme splits the input image into n+1 number of images which consists of n ROI image tiles and one residual background image tile. The encoder sends the encoded ROI image tile first and it sends the background tile, after sending all the ROI tiles. Initially the receiver decodes the ROI of the image and displays it to the user, and then the background is decoded. Therefore once the receiver started to receive the encoded image, the user can first view the ROI. The ROI compression ratio of ROI encoded image is computed with jpeg as the reference which is the ratio of memory size of ROI encoded image to memory size of jpeg encoded image. The compression ratio of ROI encoded image with different bpp is examined in ROI of size 150x150 in knee MRI image of memory size 192KB and image size of 256x256. At diverse ROI resolution, the ROI compression ratio of ROI encoded image is calculated. The graph plotted between compression ratio and bits per pixel (bpp) is illustrated in Fig.7. The green line in the graph represents ROI compression ratio with jpeg as reference and blue line represents compression ratio with uncompressed image as reference. In Fig.8, the images with ROI encoded with diverse resolution are given.

The compression ratio of the ROI encoded image with different background resolution is examined. Fig.9 shows the images produced with different background resolution. From Fig.9, it is clear that encoding the background image with very low resolution does not cause inconvenience to the observer.

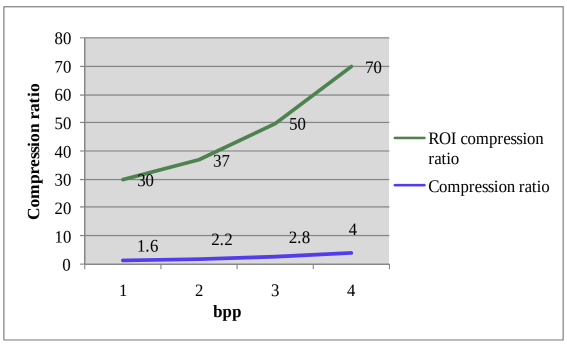

Fig. 7. Compression ratio vs bpp

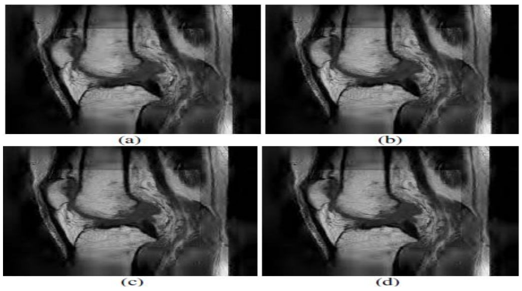

Fig. 8. ROI encoded knee MRI image of size 256x256 and ROI size 150x150 with background resolution of 0.2 bpp. (a) ROI with resolution 0.5 bpp (b) ROI with resolution 0.75 bpp (c) ROI with resolution 1.0 bpp (d) ROI with resolution 1.5 bpp

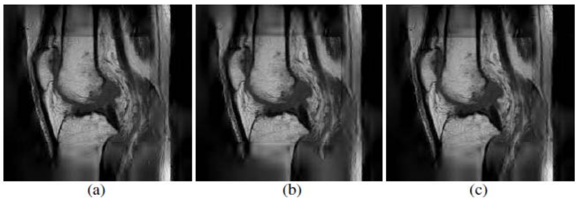

Fig. 9. ROI encoded image with different background resolution (a) background resolution 0.02 bpp (b) background resolution 0.1 bpp (c) background resolution 0.2 bpp

The performance of the proposed ROI encoding scheme is also evaluated with the aid of real world images. Fig.10(c) shows the Lena image with face as ROI. The ROI (face) is encoded with 1bpp and the background is encoded with 0.2 bpp. From the results, it is obvious that encoding background with low resolution dose not have more impact on the overall subjective quality of the image.

Fig.10. ROI encoding in real world image (a) original Lena image with uniform resolution (b) Compressed image (0.2 bpp) (c) Encoded image using proposed ROI encoding (1 bpp for ROI and 0.2 bpp for background)

VI. Conclusion

The application of ROI coding in the field of telemedicine is proposed in this paper. For each ROI, an efficient ROI encoding scheme with diverse resolution is proposed in this article. The renowned wavelet based image encoding scheme SPIHT is used by the proposed encoding scheme. The ROI coding commences with the selection of ROI and its corresponding resolution by the user. The diverse ROIs are encoded with diverse resolution (bpp) by applying lifting wavelet transform and SPIHT. By integrating all the encoded ROI image data, encoded background image and a header that contains the number of ROIs, co-ordinates and resolutions of each ROI, the final encoded data is formed. In the decoder, using the encoded data and the information available in the header, each ROI is decoded. In the decoded image ROI data are located in their corresponding places, by using the co-ordinate details in the header. The experimental results illustrate that using lifting wavelet transform and SPIHT, the proposed ROI encoding scheme provides high compression ratio and quality ROI.

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