# MR image compression with ROI decoding, SNR and Spatial scalability

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## ABSTRACT

This paper presents an algorithm that performs lossless compression of 3D magnetic resonance (MR) images and is capable of performing user selectable region of interest decoding together with spatial and signal-to-noise ratio (SNR) scalability. Selective decoding is achieved by segmenting the 3D MR image into blocks of size 16x16x2 in spatial domain and by separately coding each of the blocks. Spatial and SNR scalability are achieved by scanning of the wavelet coefficients in proper order, together with storing the markers for the bit stream generated. The encoding operation is performed only once for a given image; the quality parameters, such as spatial resolution, SNR resolution and the region of interest, can be defined at the time of decoding.

*Index terms:* MR image compression, spatial scalability, SNR scalability, region of interest, integer wavelet transform.

## 1. INTRODUCTION

Medical imaging modalities such as Magnetic Resonance (MR) imaging generate a large amount of data. The data is increasing exponentially as the imaging modalities are playing a vital role in medical diagnosis. In this scenario, data compression and storage become important issues. Further, quick access of the compressed data and transfer of the same over the network are also critical. It is quite helpful to the radiologists if tools are available so that they can preview (in the form of thumb nails) the data quickly and access only the region of interest without the need for getting the other parts of the image. When encoding medical images, it is important to remember that medical professionals do not prefer lossy compression due to possible loss of vital information. Hence, ideally the images should be coded losslessly. It is advantageous, if the lossless encoder is designed in such a way that it enables progressive decoding, together with user selectable decoding area and resolution scalability. This paper presents an algorithm to accomplish the same.

Usage of integer wavelet transform together with bit plane coding has become a well established approach to medical image compression. Several techniques have been developed and a few of them are even accepted as standard references. Notable among them are, Set Partitioning in Hierarchical Trees (SPIHT) [1], Embedded Zero tree Wavelet (EZW) [2] and Embedded Bit Coder with Optimal Truncation (EBCOT) [3]. Adaptations of these works to 3D volume data compression are also being carried out. Another technique that is adapted in this work is [4], wherein the intraband correlation is exploited and bit plane coding is carried out. Srikanth et. al. [5] extend the algorithm in [4] to carry out object based coding, wherein the background part of the MRI (air component) is not coded. In a somewhat similar fashion, object based coding of only the brain part of MRI is carried out in [6] by using a modified version of Layered Zero Tree coding. All these works focus on efficient coding of the MR images, striving for maximum compression with progressive coding as the useful bi-product.

Providing random access decoding or selective decoding is attempted by several researchers [7 – 10]. In [7] and [8], lossy compression is implemented using vector quantization and the technique of zero bit coding is employed. A good analysis of various transforms and coding schemes with respect to coding efficiency and accessibility attributes is given in [9], with main emphasis on the Lifting-based Invertible Motion Adaptive Transform (LIMAT) framework [11] and the EBCOT [3]. Leung [10] adapts the SPIHT algorithm [1] to provide random accessibility, spatial scalability and SNR scalability. Both [9] and [10] provide lossless reconstruction capability. These algorithms attempt to identify the wavelet coefficient tree corresponding to the image pixels and encode the tree individually. For lossless reconstruction, the wavelet trees include coefficients associated with adjacent trees. This overlapping of coefficients increases with the number of wavelet decomposition levels. This results in more number of coefficients to be encoded than present in a given image segment.

## 2. OESD ALGORITHM

This paper presents an algorithm that achieves selective region-of-interest (ROI) decoding, spatial scalability and SNR scalability. The algorithm modifies the ideas presented in [4] and [5]. To overcome the coding overhead associated with the aforesaid approach of encoding wavelet coefficient trees, we segment the image in the spatial domain, and encode the segments individually. As there is no overlap, each wavelet coefficient is encoded only once. When a user defines a ROI, only those bit streams corresponding to the segments that fall (even partially) within the ROI are sent to the decoder. This results in perfect reconstruction of the ROI with few additional pixels in the border area also being decoded. In case the ROI coincides with the borders of the segments, only the needed pixels are decoded. It may seem that using the concept of tiling in spatial domain and encoding, rather than working in the wavelet domain to achieve random access, is counter-productive since the wavelet decomposition of a small segment may not help decorrelating the image, thus drastically reducing the compression performance. However, the results show that this is not really so, and even though the compression ratio does come down, it is only marginal. The advantage of having random access capability far outweighs this small decrease in performance.

Spatial scalability is the ability to present the original image at lower spatial resolutions. 2D wavelet decomposition provides spatial scalability with the low-low (LL) band representing the lower resolution image. SNR scalability is the ability to decode only a selected set of bit planes so that the approximate image representation can be provided at full spatial resolution. In general, in progressive lossy to lossless coding, the bit stream is ordered to achieve progressive decoding and hence to provide SNR scalability. If the order is changed to achieve spatial scalability, SNR scalability cannot be achieved. We solve this by ordering the encoded bit stream to provide SNR scalability, but storing pointers to the bit stream that helps to provide spatial scalability also.

The bit plane coding is performed individually for each sub-band, starting from the lowest LL band, with each subsequent band being scanned in a zig-zag manner. When scanning of all the sub-bands for a given wavelet resolution is completed, the end of bit stream list is remembered, which, on requirement, is passed on to the decoder.

Encoder in the algorithm in [5] generates four lists, namely lattice significance list, magnitude list, sign list and refinement list. Because of grouping, the advantage it provides is that the entropy of the bit stream would be slightly lower resulting in marginally lower bits per pixel. However, if we adopt the same, due to the additional requirement of sending the pointer list for SNR scalability, the cost of maintaining four pointer lists would be high. It is seen that the encoder generates the bit stream in such an order that the four lists can be merged into one. With this, only one pointer list is generated and this adds a marginal overhead to the overall bit rate.

We call our algorithm Once Encoding and Selective Decoding (OESD), since the encoding is performed once that provides for selective decoding of either a given region of interest, or for a given spatial resolution, or for a given SNR resolution.

## 2.1. Encoder

1. In 3D MR image set, mask for each of the 2D images is generated by identifying the respective foreground and the background. For all the 2D images, the background is marked zero and is not coded.
2. The masked 3D image is divided into 3D segments of defined size. The 3D image mask is also divided into segments of same size.
3. Each segment is coded using the following algorithm, to which the corresponding segment of the mask is also fed.
   - 3.1. 3D integer wavelet transform is applied to each 3D image segment. 3D mask segment is also wavelet transformed.
   - 3.2. Wavelet transform of the mask segment is applied to the wavelet transformed image segment to mark the coefficients corresponding to the background as Do Not Care.
   - 3.3. The wavelet transformed image segment is divided into a 3D lattice of size v by v by t. Here v is the lattice dimension in the spatial direction (2D) and t is the lattice dimension in the temporal direction.
   - 3.4. For each 3D lattice k, the maximum of the wavelet coefficients, Wmax, is found. Threshold $T_k$ for the lattice is computed as $T_k$ = floor($\log_{10}$(Wmax)).
   - 3.5. The maximum of all the thresholds is stored as the global threshold, $T_g$.
   - 3.6. The wavelet transformed image is scanned starting from the lowest resolution. Within each resolution level, the wavelet bands are scanned in zigzag manner, starting from the LLL band. Within each band, the 3D lattices are scanned in raster scan order first in spatial direction and then in temporal direction. The 3D lattices with all the coefficients marked as Do Not Care are skipped.
   - 3.7. For every wavelet resolution, all the bit planes are scanned starting from the bit plane represented by the maximum of the threshold.
   - 3.8. ***SIGNIFICANT PASS*** :
     - 3.8.1. Check for the significance of the 3D lattice; it is significant, if at least one of its coefficients is greater than or equal to $2^{T_g}$. If it is not significant, store 0 in list 'lis' (indicating lattice insignificance). If the 3D lattice is first time significant, store 1 in the list 'lis'. Else, if the lattice is already significant, do not store anything, since the information regarding the significance is already stored.
     - 3.8.2. If the 3D Lattice is significant, check for the significance of each of the

coefficients. A coefficient is significant, if its magnitude is greater than or equal to $2^{T_g}$.

3.8.3. If the coefficient is significant, store 1 in the list 'lis'. Also, if the coefficient is positive significant, store 0 in 'lis'; otherwise store 1.

3.9. ***REFINEMENT PASS:*** Store the current bit of all the significant coefficients (at the previous threshold) in the list 'lis'.

3.10. If $T_g$ is 0, go to next step; otherwise, set $T_g = T_g-1$ and go to step 3.7 above.

3.11. After completing all the bands of the current wavelet resolution, store the next index of the list 'lis' in index_list. Repeat steps from 3.7 for the next resolution.

4. The output obtained is arithmetic coded.
5. Along with the list 'lis', the threshold array, image size, and the chain coded image mask are required to be sent to the decoder.

## 2.2. Decoder

1. Decoding can be performed by simply reversing the operations corresponding to encoding.
2. Identify and list the 3D segments that fall within the ROI selected. The segments that partially fall within the ROI are also listed.
3. Decode each of the segments.
   3.1. If spatial scalability is asked for, then decode only up to the desired wavelet resolution.
   3.2. If SNR scalability is asked for, then, starting from the lowest wavelet resolution, for each level, decode only up to the required bit plane. Then skip rest of the bit planes, and go to the next wavelet resolution.
   3.3. If both scalabilities are asked for, then, combination of steps 3.1 and 3.2 are performed.
4. If lossy decoding of the image area outside the ROI and lossless decoding of the ROI are needed, then, the segments within the ROI are decoded lossless; for the other segments, step 3 is followed with desired scalability parameters.

# 3. RESULTS

Experiments are conducted on MR images obtained from NIMHANS, Bangalore. The data consists of a set of 32 sagittal MR images of head, each of size 256x256 pixels, with 8-bit resolution. For all the experiments, the (2,2) bi-orthogonal integer wavelet transform is used. Number of wavelet decomposition levels is 2 in the spatial direction and 1 in the temporal direction. A pair of adjacent slices is considered for a group. Size of the 3D lattice used is 4x4x1. Lossless encoding is performed.

The 3D algorithm in [5] is applied on all the 32 images. The compression obtained is 2.08 bpp.

**Table I – Encoder Performance of Srikahth's algorithm [5] for four different cases.**
OA = Original Algorithm, SLE = Single list encoder, OA-EC = Original Algorithm with entropy coding after entire bit plane encoding, SLE-EC = Single list encoder with entropy coding after bit plane coding.

| | OA | SLE | OA-EC | SLE-EC |
|---|---|---|---|---|
| Average bpp | 2.08 | 2.12 | 2.17 | 2.20 |

**Table II –Performance of OESD Encoder as a function of the size of the segment.**
OA = Original Algorithm, SLE = Single list encoder, IH = Including Overhead due to storing Markers, EH = Excluding Overhead due to storing Markers. Segment size in temporal direction is 2.

| Segment size | 16x16 | 32x32 | 64x64 | 128x128 | 256x256 |
|---|---|---|---|---|---|
| Avg bpp of OA – IH | 2.59 | 2.38 | 2.31 | 2.31 | 2.17 |
| Avg bpp of OA – EH | 2.31 | 2.30 | 2.29 | 2.30 | 2.17 |
| Avg bpp of SLE – IH | 2.43 | 2.36 | 2.34 | 2.33 | 2.20 |
| Avg bpp of SLE – EH | 2.35 | 2.34 | 2.33 | 2.33 | 2.20 |

**Table III – SNR Scalability results : Performance of OESD algorithm for different SNRs.**

| SNR Scale | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| # Bit Planes | 8 | 7 | 6 | 5 | 4 | 3 |
| Avg MSE | 0 | 0.7 | 3.1 | 13.3 | 51.1 | 165.2 |
| Avg PSNR, dB | - | 49.9 | 43.4 | 36.9 | 31.1 | 26.0 |

Here the lists generated at the end of every bit plane scanning are entropy coded. Instead, if the lists are entropy coded after complete scanning, the average bits per pixel increases to 2.17 bpp. When the algorithm is modified to generate a single list and entropy is estimated at the end of every bit plane coding, the bit rate obtained is 2.12 bpp. This is attributed to the slight increase in the entropy in both the cases. When both of these modifications are combined, the rate increases to 2.20 bits per pixel.

In our case, the entropy is calculated at the end of complete coding of each segment. Table II lists the performance achieved in bits per pixel for different sizes of the segment. Note that with respect to the implementation in [5], for 16x16x2 segment size, the average bit rate increased slightly to 2.59 bpp. This is attributed to the limited area of image that we have chosen for each segment, and overhead due to the requirement of storing the markers. Contrary to the general thinking that increasing the segment size should reduce the bits per pixel, Table II shows that

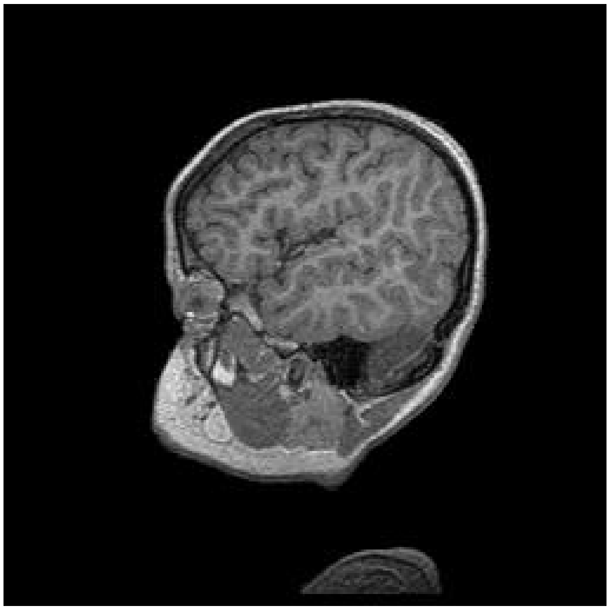


Image reconstructed at full scale

Image reconstructed at half scale

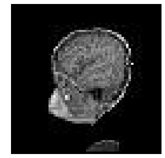
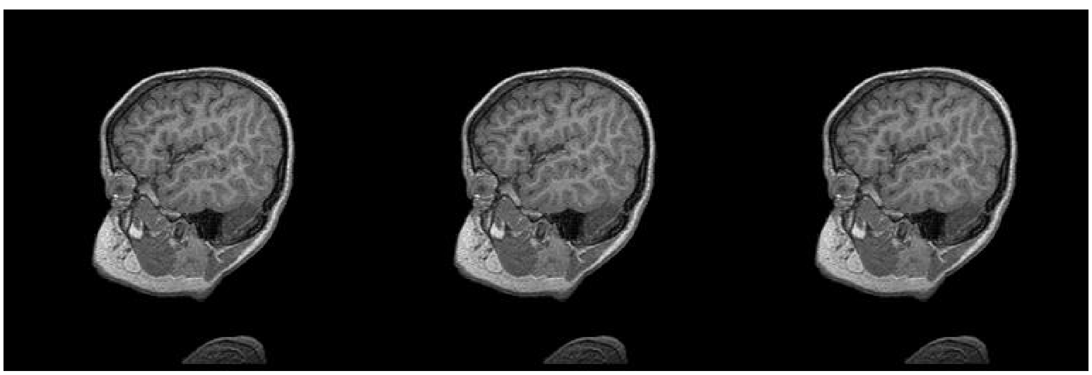
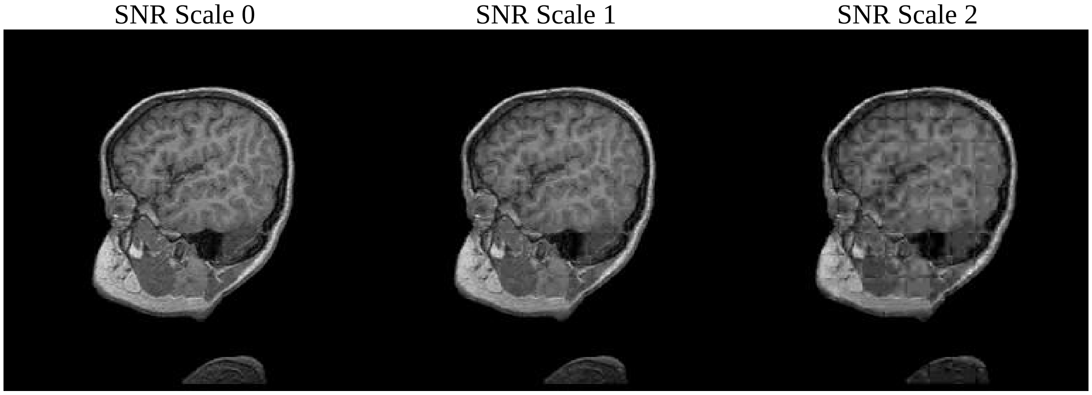


Image reconstructed at 1/4th scale

**Figure 1. Spatial Scalability of OESD : Output images for different scales.**



SNR Scale 0 SNR Scale 1 SNR Scale 2



SNR Scale 3 SNR Scale 4 SNR Scale 5

**Figure 2. SNR Scalability of OESD: Output images for different SNR scales.**

it remains fairly constant (excluding the overhead due to markers), coming down only for the segment size of 256x256x2 corresponding to entire image considered as a single segment (same as that of Table I).

It can be noted that if the implementation of [5] is used, the index list would consist of 2 rows and 4 columns for each of the 256 segments. The maximum value for any of the index is seen to be around 300; so a minimum of 9 bits are needed to represent the index. This amounts to a total of 18432 bits for an image, resulting in 0.28 bpp per image. Instead, if the single list algorithm is used, index array for each segment would be only 2 elements (for each wavelet resolution). As the maximum value of index is observed to be 550, 10 bits are needed to represent the index. This amounts to a total of 5120 bits or 0.08 bpp. Hence, the single list approach compensates for the increase in the bpp that is associated with the choice of the segment size.

One can argue that the choice of 32x32x2 segment size would reduce the number of bits to be allocated for index representation. However, this would provide a coarser ROI selection at the time of decoding, with only a marginal reduction in bpp. So the optimal segment size is 16x16x2. This results in an overall overhead of around 0.35 bpp when compared to the original algorithm (including the 0.08 bpp overhead of storing the index values); this is the price that needs to be paid for the user selectable features that the algorithm provides. It can be noted that this cost affects the decoder only when it attempts complete lossless decoding of the image.

With a segment size of 16x16x2, the possible number of levels of wavelet decomposition is 2. With this, the available spatial scales are 1:1, 1:0.5 and 1:0.25. Figure 1 shows the results of decoding a sample image for all the three available spatial scales. The average performance with respect to SNR scalability for 32 images in terms of mean square error and peak signal to noise ratio (PSNR) are shown in Table III. Figure 2 illustrates the SNR scalability results for a sample image. It can be seen that, for SNR scales of 1 to 3, the decoded image is visually indistinguishable from the original image (the decoded image with scale 0). Even with SNR scale of 4, only very small blocking artifacts are visible, which become distinct only with SNR scale of 5. The image quality worsens beyond acceptable limits for SNR scales of 6 and 7, which is akin to representing the image with only one/two bit planes. Note that these blocking artifacts are due to spatial domain segmentation and large approximation due to ignoring the bit planes.

## 4. CONCLUSION

We propose a wavelet based algorithm called Once Encoding with Selective Decoding, which features Region of Interest selection, SNR scalability and spatial scalability at the decoding time. The algorithm encodes the image only once. At the time of decoding, user can select the ROI or the amount of scalability desired and decode only what is required. Experiments on real MRI data from National Institute of Mental Health and Neurosciences, Bangalore show that the algorithm provides these features with a marginal encoding overhead of around 0.35 bpp.

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