Tumor Preserving Medical Image Compression

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ABSTRACT

Medical imaging involves handling of huge volumes of DICOM images. Main agenda is to compress the images without compromising on the quality of the image. In this paper, a comparative analysis of different compression techniques is made for medical DICOM images. Lossless compression based on General indexing and Huffman gave maximum compression ratio 1.6 and 1.85. The proposed lossy compression is based on db1, db2 wavelet at single level decomposition. The proposed technique is computationally efficient since it uses a simple algorithm, at the same time achieving good PSNR, compression ratio and bits per pixel (bpp). The PSNR achieved with the proposed algorithm is always above 54.5db across all test images. The results obtained clearly indicate that the proposed technique preserves the tumor region, thus not affecting medical diagnosis. Thus further processing like segmentation, tumor detection and classification can be applied on these compressed images.

Keywords

Tumor detection, lossy compression, Wavelet, Huffman

1. INTRODUCTION

MRI (Magnetic resonance imaging) is the most widely used method in medical diagnosis. In the medical imaging MRI images are voluminous. Each image requires a large amount of storage and collectively a patient's record may require many images to be stored. So to reduce the storage space compression is done. In case of medical imaging the most important requirement for any compression technique is to preserve the ROI (region of interest) which in our case is the tumor part so that medical diagnosis must not be affected thus maintaining the quality of the image. An image compression technique can be classified as lossless or lossy.

In lossless compression no data is lost i.e. image is reconstructed perfectly. As compared to the lossless compression technique the lossy techniques are more efficient in terms of compression ratio. In this the required image characteristics are usually preserved in the coefficients of domain space in which original image is transformed into. In DWT (Discrete Wavelet Transform) image compression the wavelet coefficients i.e. approximation coefficients keep all the information needed for reconstructing the medical image. To achieve maximum compression ration only the approximation coefficients are saved discarding others. The different parameters to judge the performance of the lossy compression technique is PSNR, compression ratio, bits per pixel, etc.

In the next section, the related work is briefed. In Section 3, the algorithms for lossless and lossy compression are described. Section 4 contains experimental results. We offer our conclusions in Section 5.

2. RELATED WORK

Ruchika et al. [1] proposed a method in which the redundancy of the medical image and DWT coefficients are reduced through thresholding and further through Huffman encoding.

In [2], Two Component Medical Image Compression Technique is implemented where some of the slices in a sequence are represented by JPEG data and some of the slices are represented by SPIHT data.

Paper [3] gives analysis of efficient wavelet based volumetric image compression.

In this paper we propose a method giving better results in terms of the compression ratio (CR), PSNR and bits per pixel (bpp).

3. IMPLEMENTATION

3.1 Lossless technique

In General indexing technique, the histogram of the image is computed and the number of non-zero intensity values is found. The number of bits to encode is log2(N), where N is the number of non-zero intensity, which is fixed across all pixels.

In Huffman coding, the histogram of the image is found and probability of intensity values is calculated. Based on these probabilities the standard Huffman algorithm is applied to generate the variable length code.

3.2 Lossy Technique

In image compression, transform coding techniques the most popular method used is discrete wavelet transform (DWT). Wavelet transform provides the time-frequency analysis simultaneously as it provides multi-resolution analysis.

The discrete wavelet transform is implemented using multirate filter banks. These filters divide a signal frequency into subbands. At each level of decomposition the approximation coefficients are generated from low pass filter and the detail coefficients from high pass filter. DWT analyzes an image across rows and columns so as to separate the horizontal, vertical, diagonal details as shown in Fig.1.

In case of single level decomposition at first stage the rows are filtered using low and high pass filters. The filtering is done using the 1-D convolution with filter coefficients; this is followed by the downsampling with factor 2. In second stage filtering is done on columns followed by downsampling with factor 2 giving the four subbands LL, HL, LH, HH. The Fig.1 shows the single level decomposition.

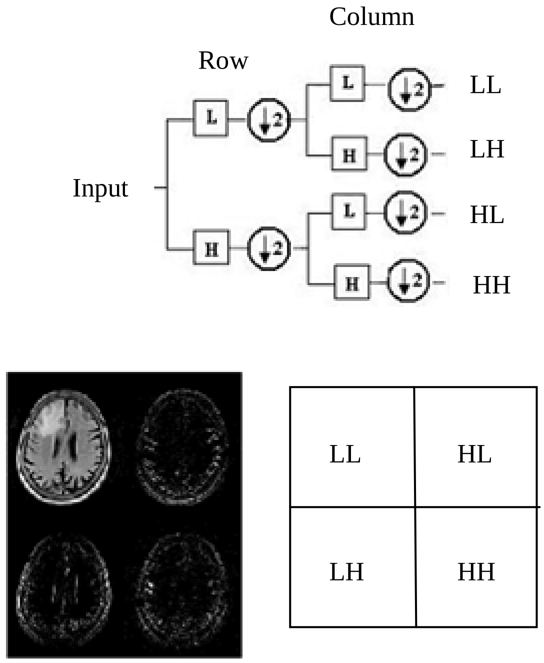

Fig.1 Single level decomposition

The single level decomposition shown in Fig.1 clearly indicates that the approximation coefficient (LL) preserves most of the information including the tumor region hence we can discard other detail information like horizontal, vertical and diagonal to achieve good compression ratio. In this paper two wavelets are examined: Daubechies 1 i.e. Haar and Daubechies 2. The wavelet functions for the Haar and Daubechies 2 as shown in Fig.2.

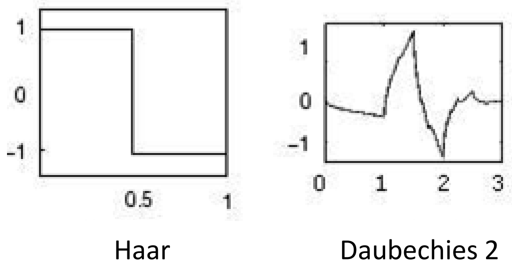

Fig.2 Wavelet functions for the Haar and Daubechies 2

The proposed wavelet based image compression algorithm is explained below:

1. Read the DICOM image
2. Decompose the image using the DWT
3. Scale the approximate coefficients
   i. If the maximum coefficient value is above 1000 then scale by factor 100.
   ii. If the maximum coefficient value is below 1000 then scale by factor 10.
4. These scaled coefficients are then quantized by thresholding.
5. The approximate coefficients are then encoded using Huffman coding technique.

The inverse discrete wavelet transform (IDWT) reconstructs the scaled and thresholded approximate coefficient. The reconstructed image based on the proposed method is shown in Fig.3, which shows that the tumor part is preserved after the reconstruction. For viewing purpose only image 1, 2, 11 and 12 are shown.

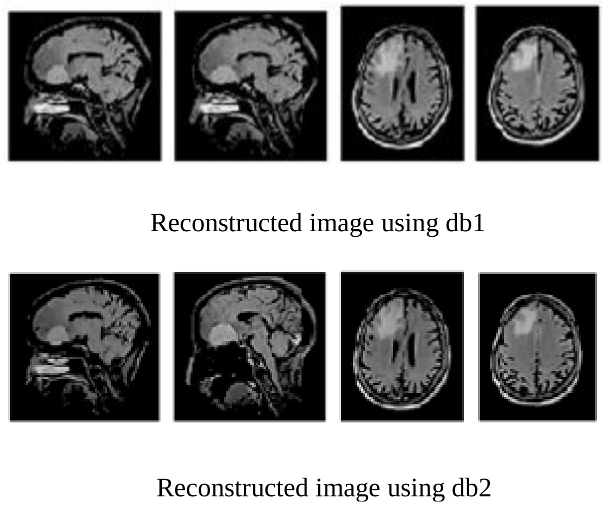

Fig.3 Reconstructed image based on the proposed method

4. EXPERIMENTAL RESULTS

The images used to test the performance of the Medical Image compression techniques are shown in Fig.4. These images are obtained from Gundiyal radio diagnostic centre, Amravati, Maharashtra, India. All the images used for testing are 16-bit unsigned integer, DICOM images. The results for lossless compression based on General Indexing technique and Huffman coding are shown in Table 1 and 2 respectively. The results for lossy compression are based on db1, db2 wavelets is shown in table 3, 4 respectively. The codes were executed on an Intel Core i5-2430 processor with 4GB RAM memory.

The parameters used to evaluate the results are defined as below:

1. **Compression Ratio (CR):**

   CR = $\frac{n1}{n2}$

   where n1 is the number of bits to represent the original image and n2 is the number of bits to represent the encoded image.

2. **Peak Signal to Noise Ratio (PSNR):**

   PSNR = $10\log_{10}\frac{(2^{r}-1)^{2}}{MSE}$

   where r is the number of bits required to represent the original image. In our case r = 16.

3. **Bits Per Pixel (bpp):**

   Bpp = $\frac{b1}{b2}$

   where b1 is the number of bits to represent the encoded image and b2 is the total number of pixels in the original image.

The maximum compression ratio achieved using simple indexing is 1.6. The average encoding and decoding time across all the 12 test images is 478.4738 and 69.6645 sec respectively. The maximum compression ratio achieved using Huffman encoding is 1.8568. The average encoding and decoding time across all the 12 test images is 680.9699 and 1001.926 sec respectively. Since both the techniques are lossless they perfectly reconstruct the image.

The maximum compression ratio achieved using db1 based wavelet compression is 40.7784. The average encoding time, decoding time, bits per pixel and PSNR across all the 12 test images is 6.6321 sec, 1.5553sec, 0.55592 bpp and 56.78475 db respectively.

The maximum compression ratio achieved using db2 based wavelet compression is 40.1415. The average encoding time, decoding time, bits per pixel and PSNR across all the 12 test images is 6.6607 sec, 1.5559 sec, 0.54659 bpp and 56.91690 db respectively.

Fig.3 shows the reconstructed images based on db1, db2 wavelet compression. The reconstructed images clearly preserve the quality of the image and more importantly the tumor region.

5. CONCLUSION

The quantitative analysis of the compression techniques clearly shows the ineffectiveness of the lossless techniques to achieve high compression ratios and less time for computation. The proposed technique based on single level decomposition uses scaling and thresholding of approximation coefficients. Thus the time for encoding and decoding required is less. The PSNR achieved is above 54.5 db across all the test images, for wavelets namely db1, db2. The maximum PSNR, CR and minimum bpp achieved by [1] is comparatively lower than that achieved by our proposed method using db1 and db2. The proposed algorithm also provides superior performance in terms of compression rate and PSNR compared to [2]. The formula used by [3] to calculate CR is different from the one used in this paper; using the formula given in [3] maximum CR we achieved is 97.54 which is much higher than the maximum achieved i.e. 79.6038 in paper [3] for MRI images. The results obtained by our proposed method clearly demonstrate that the superior quality images can be obtained preserving the tumor region. Hence further processing like segmentation, tumor detection and classification can be applied on these compressed images.

6. REFERENCES

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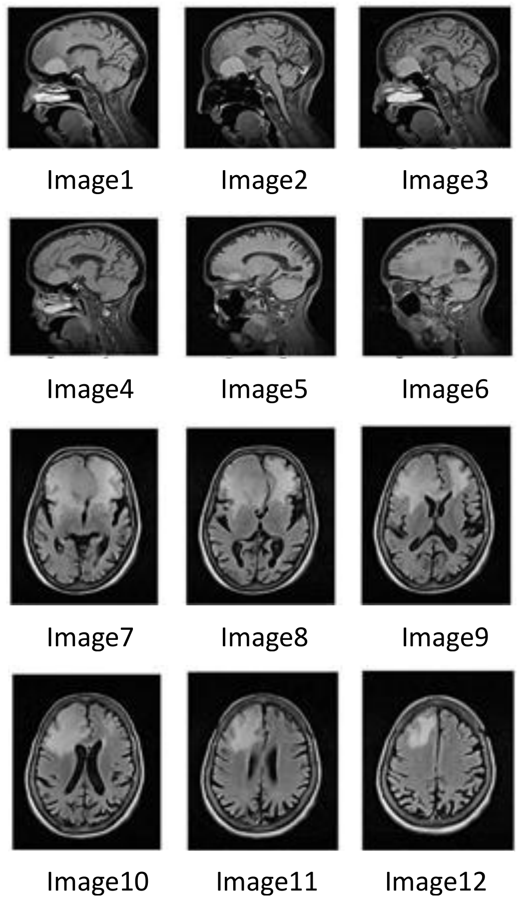

Fig.4 Medical DICOM MRI Image dataset

7. RESULT TABLE

Table 1: Results for General Indexing Technique for compression

Uncompressed Size (bits)	Compressed Size (bits)	Reduction (Bits)	Compression Ratio	Encoding Time (sec)	Decoding Time(sec)
1048576	655360	393216	1.6	562.0862	77.6191
1048576	655360	393216	1.6	562.2000	77.6724
1048576	720896	327680	1.4545	616.4801	77.8448
1048576	655360	393216	1.6	563.5485	78.1681
1048576	655360	393216	1.6	566.2837	76.2985
1048576	655360	393216	1.6	560.8659	76.4253
819200	563200	256000	1.4545	372.4082	60.4516
819200	563200	256000	1.4545	376.7383	59.9724
819200	563200	256000	1.4545	372.3132	60.0037
819200	563200	256000	1.4545	373.6025	59.5371
819200	563200	256000	1.4545	403.2066	64.8760
819200	563200	256000	1.4545	411.9523	67.1044

Table 2: Results using Huffman Coding

Uncompressed Size (bits)	Compressed Size (bits)	Reduction (Bits)	Compression Ratio	Encoding Time (sec)	Decoding Time(sec)
1048576	577017	471559	1.8172	768.5243	1050.0715
1048576	565831	482745	1.8531	713.7882	850.46751
1048576	581776	466800	1.8024	776.9908	1072.0843
1048576	576830	471746	1.8178	792.5192	975.83228
1048576	570095	478481	1.8393	751.3045	844.28525
1048576	564710	483866	1.8568	745.5834	853.56505
819200	466408	352792	1.8531	619.8670	1147.9347
819200	468265	350935	1.7494	615.1288	1073.6692
819200	456515	362685	1.7944	606.1636	1108.7721
819200	451380	367820	1.8148	601.3731	1064.2832
819200	459898	359302	1.7812	601.5242	997.59101
819200	453047	366153	1.8082	578.8711	984.55619

Table 3: Results using 'db1' wavelet for compression

Uncompressed Size (bits)	Compressed Size (bits)	Reduction (Bits)	Compression Ratio	Encoding Time (sec)	Decoding Time(sec)	Bits per pixel (BPP)	PSNR (db)
1048576	33993	1014583	30.84682	7.848655	1.513111154	0.518692017	56.2589
1048576	33207	1015369	31.57696	7.544755	1.46611489	0.506698608	57.34741
1048576	34130	1014446	30.723	7.685736	1.513738906	0.520782471	55.72597
1048576	33470	1015106	31.32883	7.771816	1.555558359	0.51071167	56.02951
1048576	28299	1020277	37.05346	7.057945	1.359156812	0.431808472	55.00055
1048576	**25714**	**1022862**	**40.77841**	**6.817879**	**1.303107327**	**0.392364502**	**54.51241**
819200	33571	785629	24.40201	5.974884	1.753992401	0.655683594	57.73823
819200	33136	786064	24.72236	5.924388	1.738727093	0.6471875	57.43998
819200	33009	786191	24.81747	5.957963	1.69516208	0.644707031	57.73033
819200	32415	786785	25.27225	5.843904	1.668441162	0.633105469	57.95229
819200	31789	787411	25.76992	5.725232	1.574762081	0.620878906	57.75982
819200	30128	789072	27.19065	5.431493	1.522110494	0.5884375	57.92162

Table 4: Results using 'db2' wavelet for compression

Uncompressed Size (bits)	Compressed Size (bits)	Reduction (Bits)	Compression Ratio	Encoding Time (sec)	Decoding Time(sec)	Bits per pixel (BPP)	PSNR (db)
1048576	31109	1017467	33.70652	7.311287	1.298308107	0.474685669	55.42735
1048576	33588	1014988	31.21877	7.747085	1.445256692	0.512512207	57.864
1048576	34512	1014064	30.38294	7.961583	1.622792767	0.526611328	56.10582
1048576	33825	1014751	31.00003	7.865699	1.647248135	0.51612854	56.43271
1048576	28689	1019887	36.54976	7.209151	1.393387656	0.437759399	55.19587
1048576	**26122**	**1022454**	**40.14149**	**6.929164**	**1.34174526**	**0.398590088**	**54.60624**
819200	32513	786687	25.19608	5.865098	1.826886408	0.635019531	57.79099
819200	32304	786896	25.35909	5.984411	1.688300431	0.6309375	57.65296
819200	31965	787235	25.62803	5.898553	1.672112739	0.624316406	57.78141
819200	31245	787955	26.21859	5.786592	1.615618953	0.610253906	57.8949
819200	30600	788600	26.77124	5.709383	1.591121678	0.59765625	57.59105
819200	30450	788750	26.90312	5.660963	1.528293076	0.594726563	58.65953