Lossless Medical Image Compression using Redundancy Analysis

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Summary
We studied two image characteristics, the smoothness and the similarity, which give rise to local and global redundancy in image representation. The smoothness means that the gray level values within a given block vary gradually rather than abruptly. The similarity means that any patterns in an image repeat itself anywhere in the rest of the image. In this sense, we proposed a lossless medical image compression scheme which exploits both types of redundancy.
The proposed method segments the image into variable block size(VBS) and encodes them depending on characteristics of the blocks. The proposed compression schemes works better 10~40[%] than other compression scheme such as the Huffman, the arithmetic, the Lempel-Ziv, HINT(Hierarchical Interpolation), JPEG-LS(Lossless Scheme of JPEG) and lossless JPEG2000.
Key words:
compression, variable block size, segmentation, redundancy

Introduction

Medical images used at medical facilities are now commonly digitalized due to corresponding advances in information technology. CT(Computed Tomography) or MRI(Magnetic Resonance Image) generates digitalized signals by its own, and diagnostic images from legacy devices can be digitalized by film scanner and such.
The size of digitalized images is varied by the image devices. CT images are mostly in resolution and RI and Ultrasonic images are usually NMI(Nuclear Medicine Imaging) is usually at low resolution, to images are commonly used. Fields utilizing digitalized medical images such as PACS(Picture Archiving and Communication System) require an economical compression technique without diminishing diagnostic values.
There are two types of image compression technique depending on whether there is information loss in the decompressed images.

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Well known JPEG(Joint Photographic Experts Group) based on DCT(Discrete Cosine Transform) is loss compression techniques with relatively high compression ratio which is done by exploiting human eye perception[2,3].
However under a special circumstance such as disease diagnostic requires medical images to be at high-resolution as possible with minimized data decompression time. Thus, rather than loss compression with relatively high compression ratio, mathematical lossless compression techniques are favored in this fields[1].
Lossless compression techniques can be implemented by entropy coding such as Huffman coding, Lempel-Ziv coding, and arithmetic coding[5,6,7]. Also HINT(Hierarchical Interpolation), DP(Difference Pyramid), Bit-Plane encoding, block coding have been proposed as lossless medical image compression techniques.
HINT is based on sub-sampling utilizing variable resolution pyramid coding. It reduces the original image's horizontal and vertical resolution to 1/2, and then encodes the lower resolution output. The lower resolution outputs are enlarged to its original resolution by interpolation to encode its difference between the enlarged images and the original image. It is a near lossless technique since each pixel of the lower resolution image is interpolated to 4 pixels on upper pyramid.
DP is also based on variable resolution model similar to HINT, consists of average pyramid and differential pyramid. However it lacks required compression ratio [4].
Techniques described above can be combined with predictive coding methods such as differential pulse code modulation to acquire higher compression ratio[2,4,8,9,10].
Commonly used Transform Coding and Vector Quantization are block based coding techniques [15]. In practice, the size of the block is heavily depends on efficiency or vector quantization practicality, and is usually fixed[14]. By varying the size of blocks based on

local characteristic of image, variable transfer coding can achieve better efficiency, these techniques modify the block size adaptively thus, called variable block methods.

The first method is to segment an image into variable blocks with its visual characteristics, dividing each block on the condition whether the block has any edges. Though this method has its visual favor, it lacks the concern for encoding efficiency.

The second method is simpler segmentation by threshold value. One of the ways to achieve this is that to segment the image by local average diversity. The others are to segment by local diversity and by neighboring diversity differences.

It is hard to detect low contrast edges with segmentation by average diversity, resulting fewer segmentation than would be needed. Other two are over sensitive to local changes, therefore segmentation may be done excessively, which means objectivity of threshold value is not easily determined.

But if the standard value is directly related to encoding characteristic, a simple threshold can be set to speed up the segmentation process.

Since the best experimental result from a typical medical image can be used with other medical images to produce similar high compression ratio, this method is well suited for medical image segmentation.

The third segmentation method is done by comparison with encoding efficiency. The last method is to segment image based on the optimization of transfer-distortion ratio, which is one of objective evaluation method of encoding efficiency.

The major difference between medical images and common data is the existence of large redundancy information. Image signal commonly holds excessive amount of redundancy information. By digital signal processing, one can remove these redundancies by compressing or encoding to achieve actual image compression.

In this study, various medical images have been segmented into variable blocks and compressed based on characteristic of each block to reduce global and local redundancy.

2. Local and Global Redundancy

Unlike common data, image signal usually holds large amount of redundancy information.

There are two types of redundancy, one is local redundancy, described by neighboring pixels do not abruptly change, but change gradually in their values. The other is global redundancy caused by similar patterns being repeated over the image.

2.1 Local Redundancy

Neighboring pixels do not change abruptly, but change gradually in their values. Illumination effect usually enforces such occurrence. This characteristic is also called smoothness.

The level of smoothness is evaluated by the difference in pixels' maximum and minimum gray level within the block or certain area of the image.

If the difference in pixels' maximum and minimum gray level is 0 within the block then the pixels have the same level of gray, thus to compress this block, RLC can be used to record repeated value and the number of times they are repeated[11].

Even if the difference is not 0, it is usually very small. Therefore this block can be represented by the offset value between the minimum gray level value and neighboring pixels in the block. Each offset can be *N*-bit encoded as shown in Eq. 1.

$$N = \lfloor \log_2 V_{th} \rfloor + 1 \qquad (1)$$

If the value is smaller than fixed threshold value, it is compressed only with minimum gray level value and corresponding offsets. Therefore it is very important to pick a proper threshold value. Figure 1 is showing image of Lena segmented by a threshold value.

Fig. 1. Example of segmentation for Lena image.

As figure 1 is shown, bigger blocks represent regions with less diversity. Regions with complex diversity are segmented into smaller blocks.

If a block gets bigger the difference between the maximum and the minimum values of pixels within the block gets bigger also.

The average distribution of the difference(D) between the maximum and the minimum values of pixels within blocks grouped by block size is shown in figure 2. It is clear that the difference distribution has a characteristic of consistency over various images. Lena, MRI, and X-ray images were used to produce figure 2.

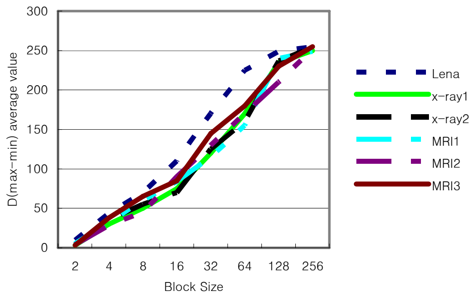


Fig. 2. Average distribution of D values according to block size.

2.2 Global Redundancy

Global redundancy is caused by patterns repeated over same image, in other words, the same brightness pattern gets repeated with statistic similarity. If one block is repeated n times within an image, the other n-1 blocks can be represented with only the coordination, thus, compression done.

Global redundancy is more prominent when the size of the block is smaller. In this study, global redundancy is only considered at the last stage, with 2×2 blocks, if any redundancy exists, 50[%] compression ratio can be achieved by just recording the blocks' coordinates. The 2×2 block has 4 pixel values and by just recording coordination, only 2 bytes can be used.

This method is used with fractal encoding. In fractal scheme, image is segmented into very small units to find a basic pattern that can be commonly used.

The similarity of the whole image must be studied to find a basic pattern. One basic pattern block of a certain size can be manipulated by geometric modifications such as magnification, reduction, rotation or brightness scaling to represent the original image.

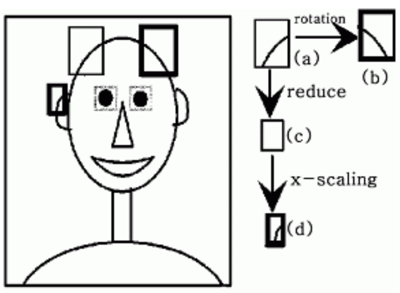


Fig. 3. An example of fractal encoder.

Figure 3 shows an example of fractal encoder. (a) can be rotated to represent (b) and by scaling (b), one can reproduce (d).

The weak point of this fractal scheme is that it takes a lot of time to encode an image. Because real time encoding is not yet practical with fractal encoding, this method keeps distance with studies concerning real-time image service, but in the fields that real-time encoding is not need such as multimedia applications or information retrieval search, this method is well studied for its high resolution and high compression ratio[12]. It is known that similarity-only compression within the same frame, it excels DCT. In this study, only the same blocks were counted as redundancy without rotation or scaling operations shown in figure 3 to reduce encoding time consumption.

3. The overall structure of the proposed algorithm

The overall flowchart of the proposed compression method is shown in figure 4. The original image is segmented into certain size(K×K) blocks and each block is processed with following procedures.

If all pixels within the block have same value, RLC is used. If the values are below the threshold only the difference is encoded. Of course, a single byte is used to record its minimum value.

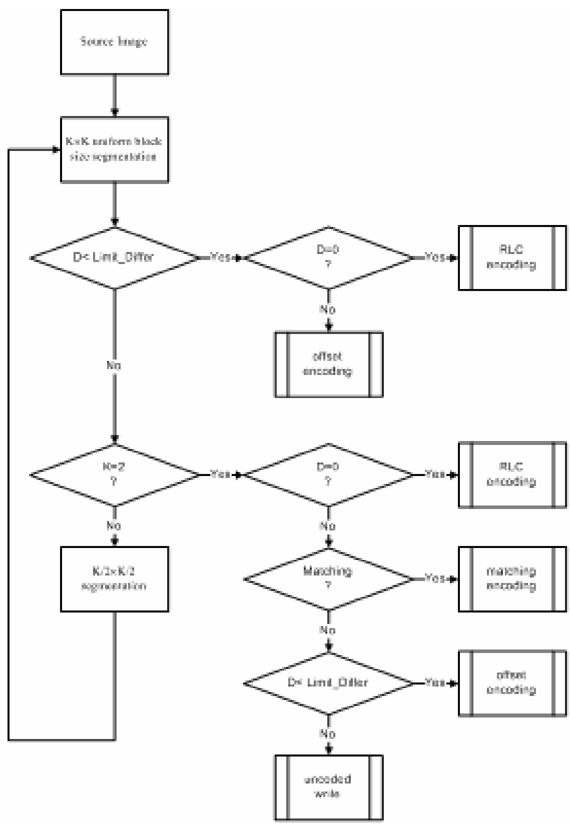


Fig. 4. Flowchart of the proposed compression scheme.

If above two conditions are not met, then the block is segmented into 4 smaller blocks (K/2×K/2). Each block is tried again with the same procedures described above.
These procedures are repeated until the block is sized into 2×2. 2×2 block has different sequence of procedures. If all pixel values within the block are identical, RLC is used, if not, neighboring blocks are looked up for an repeated block. If identical or repeated block is located, the distance between is recorded. if these two conditions are not met, then the threshold is checked. If the value is bellow the threshold, the difference is recorded. If all the conditions get failed, the block is not compressed at all. If 2×2 blocks are treated as same as bigger blocks applying threshold value check procedure at first, the global redundancy would not be taken into account efficiently, thus, compression ratio falls. It is necessary to reduce enough global redundancy at 2×2 blocks.
Storing a large number of small neighboring blocks in the memory to find out whether there is a repeated block around causes not only memory capacity problem but also consumes a longer search time, therefore a moderate memory capacity is more than efficient enough. A large memory buffer for those small blocks does not so much affect the compression ratio. And dynamic Huffman encoding is used for efficient header information.
Figure 4 is explained as following. The original image is segmented into K×K blocks. This segmented image is the input source image for the proposed compression method. The threshold value(Limit_Differ) was chosen through experiments. If the difference(D) between the maximum and the minimum values of the pixels within the block is less than the threshold value(Limit_Differ) and D is 0 then RLC is applied. If D is not 0, offset is used to encode. if D is bigger than the threshold value(Limit_Differ), then the block is again segmented into 4 smaller blocks and the procedures are repeated.
These procedures are repeated until the block size become 2×2. For 2×2 block, if D is 0 then RLC is applied, if not followings are checked.
From the search for repeated block among its neighbor, if repeated block is located, only the coordination is encoded. If it is not found, the value is checked against threshold. If it is less than the threshold, offset encoding is performed, if larger, no compression is done to the block.
Only the identical block is searched among neighboring blocks at the last stage, but if the similar block is checked instead, near lossless compression can be achieved.

4. Experimental Results

Increasing memory buffer for 2×2 block procedure, which is the last step in the proposed image compression, also enhances compression ratio. However it also consumes a large amount of time. To optimize the size of buffer against compression ratio and time consumption, following tests had been performed.
Figure 5 shows the average on the number of repeated blocks over seven different medical images. if the size of buffer is bigger than 2, then the average number of repeated blocks stays stable, which suggests repeated blocks are usually found close to the current pixel. In this study, the size of buffer was set to 16, which does not produce much difference in time consumption compared to other methods.

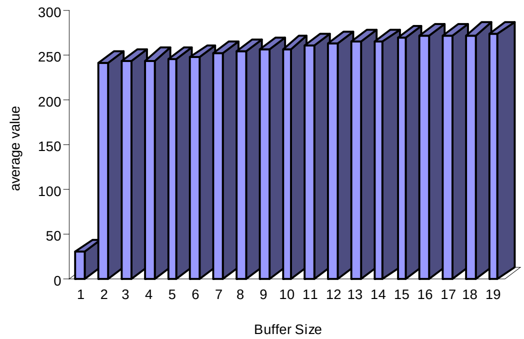


Fig. 5. The average value of repeating blocks according to buffer size.

Proposed procedure sequence for last 2×2 block is very important for global redundancy reduction, If the same procedure sequence applied to bigger blocks were applied to 2×2 block, the global redundancy would be hardly accounted for. Figure 6 shows the increased difference in compression ratio between applying proposed sequence and applying the same sequence as bigger blocks. The figure clearly displays increased compression ratio when proposed sequence was applied.

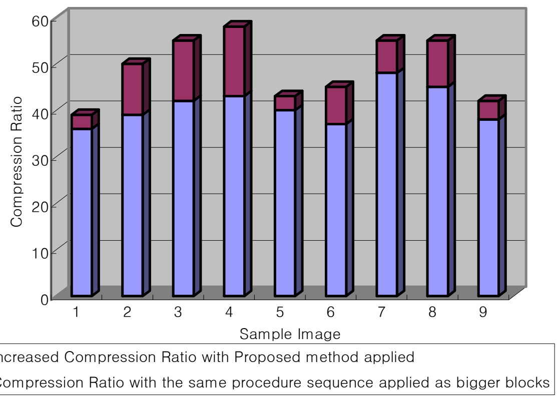
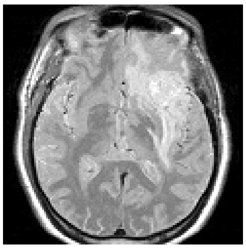


Fig. 6. Compression ratio using global and local redundancy.

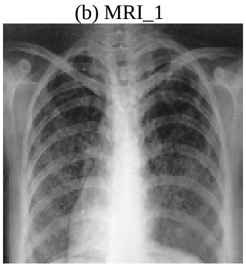
When the same sequence was applied to 2×2 blocks as bigger block, the compression was mostly done by local redundancy reduction. The increased amount with proposed sequence was resulted by both local and global redundancy reduction.

(a) Lena



(b) MRI_1

(c) MRI_2



(d) X-ray1

Fig. 7. General images used in experiment.

Figure 7 shows typical images of Lena, MRI, and X-ray used in the test. To evaluate the proposed algorithm, CP(Compression Performance) is displayed in Table 1 and Table 2. Eq. 2 shows equation used to produce CP[12].

$$CP = \frac{a-b}{a} \times 100 \tag{2}$$

In Eq. 2, a is original image size and b is compressed image size.

Various other methods are compared, as listed bellow.

- H : Huffman coding scheme(without a predictor)
- LZ : Lempel-Ziv(Unix Compression) scheme
- LZ77 : Unix Gzip scheme
- JPEG-LS : Absolutely lossless compression scheme with 1st order predictor.
- HINT: Hierarchical Interpolation
- JPEG2000 : lossless JPEG2000 code-streams use the reversible 5/3 wavelet transform with 5 levels of decomposition, with a layer progressive code-stream having 7 quality layers[13].
- P : Proposed scheme.

The comparison between these methods and the proposed method are charted on Table 1 and Table 2.

As shown in Table 2, LZ and LZ77 with dictionary methods have better compression ratio with X-ray images. That is because other method utilizes neighboring pixel values directly, dictionary method builds a value dictionary from various pixels, thus low resolution images - which also means less diversity with images - like X-ray images are favored with dictionary methods[4]. However the proposed method provides reliable compression ratio with high resolution images such as MRI, as well as low resolution images, like X-ray images.

Table 1: Compression ratio for Lena and MRI images [Unit : %]

	H	LZ	LZ77	JPEG -LS	JPEG 2000	HINT	P
Lena	7	6.69	10.6	34	33	37	42
MRI_1	14	28.75	28.5	44	42	45	49
MRI_2	22	40.83	43.1	49	47	45	55
MRI_3	22	43.84	46.6	54	53	51	60
MRI_4	9	15.8	15.8	36	33	42	44
MRI_5	7	12.4	12.4	32	30	45	45
MRI_6	16	24.9	24.9	43	44	53	54
MRI_7	18	28	28	46	45	48	56
MRI_8	9	15	15	37	36	37	40

Table 2: Compression ratio for X-ray images [Unit : %]

	H	LZ	LZ77	JPEG -LS	JPEG 2000	HINT	P
X-ray1	48	64.5	63.3	46	45	53	64
X-ray2	48	62.67	62.3	46	45	55	63
X-ray3	49.8	65.67	64.5	45	44	43	61
X-ray4	43	63.50	61.8	45	45	48	64.7
X-ray5	49	62.06	60.9	44	45	45	63
X-ray6	45	63.28	61.8	44	43	48	59
X-ray7	47	62.74	61.4	45	44	48	63
X-ray8	49	64.52	63.38	43	43	52	65

Figure 8 is showing the time consumptions with various compression methods. These are average time taken to compress MRI, X-ray images and such. The test was done on Intel 1.5Ghz processor and programmed in C++.

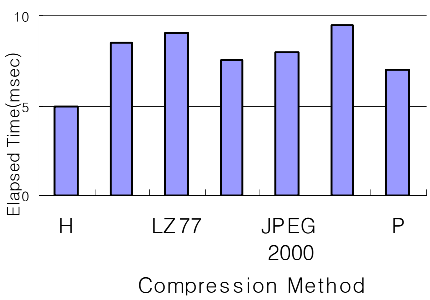


Fig. 8. The Elapsed time during the compression.

5. Conclusion

Common block coding stresses on global redundancy removal to achieve its compression ratio, however in this study, proposed image compression scheme with variable block removes local and global redundancy to achieve higher compression ratio without major time consumption difference compared to other compression schemes.

The most important variable in proposed algorithm is the threshold value D. Since the initial size of block is 8×8 and the differences between the maximum and the minimum values within blocks are not large and actual compression in done in unit of bit, 2^n can be set as threshold value.

Since threshold value from 10~16 range produced most preferable compression ratio with medical images, value of 16 was chosen for this study. The buffer size for searching repeated block was set to 16 for speed. With these variable, proposed algorithm produced 17~40[%] compression ratio improvement over LZW, Huffman, JPEG-LS, JPEG2000 on MRI images and 8~20[%] improvement on X-ray images. Proposed algorithm can also be adapted to lossy compression scheme. Altering repeated bock search procedure to look for not exactly identical block, but block with small enough difference, lossy compression scheme can be achieved. Other application would be image archive retrieval. Using the compression ratio as the key index to images, selected image can easily be retrieved. This can also be used for image assortment. Unlike other transfer coding methods, the compression ratio also represents complexity or entropy of the image with proposed method, the compression ratio may be used to sort and index image archives.

Acknowledgments

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