

Development of Near Lossless Coding Algorithm for Medical Images using Grayscale and Binary Matrices

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ABSTRACT:

Lossless compression techniques can be implemented by entropy coding such as Huffman coding, Differential Huffman coding, Lempel Ziv coding, Run length coding ...etc. In this paper, a new near lossless image coding algorithm using different technique will be presented. Our coding algorithm is based on two matrices formulations only, which are Gray Scale Matrix (GSM) and Binary Matrix (BM). Those matrices have been used for encoding and decoding process. As a result the computational complexity is greatly simplified, therefore producing a very fast coding and encoding processes.

This algorithm is most suitable for those images where lossy compression is avoided such as medical images used for teleradiology and telemedicine purposes. Different MRI images have been tested. The performance of the proposed algorithm is evaluated using the compression ratio (CR) and peak signal to noise ratio (PSNR). The obtained simulation results showed that a compression ratio of 6.35:1 to 13:1 was achieved without affecting the quality of the clinical information.

Keywords: *lossless compression, Huffman coding, medical image, teleradiology, Binary Matrix (BM), Grayscale Matrix (GSM).*

الملخص

يمكن تصميم طرق ضغط البيانات بدون فقد بواسطة ترميز الانتروبي والذي يشمل ترميز هوفمان و ترميز هوفمان التفاضلي وترميز لامبيل زيف و ترميز طول التكرار, وغيرها. في هذه الورقة سيتم عرض طريقة مستحدثة مبنية على تكوين مصفوفتين فقط هما مصفوفة التدرج الرمادي والمصفوفة الثنائية بحيث يتم استخدامهما في عمليتي الترميز وفك الترميز. نتيجة لذلك فقط تم تبسيط العمليات الحسابية وبالتالي زيادة سرعة تنفيذ العمليتين المذكورتين. تعتبر هذه الطريقة مناسبة جدا للصور الطبية المستخدمة في مجال الكشف والتطبيب عن بعد والتي تستلزم عدم فقد تفاصيل بياناتها عند اقيام بعملية الضغط. كفاءة الطريقة المقترحة تم تقييمها بواسطة قياس نسبة الضغط ونسبة الاشارة الى التشويش بعد تطبيقها على مجموعة من صور الرنين المغناطيسي. النتائج المتحصل عليها تبين ان افضل نسبة ضغط للبيانات تم الحصول عليها تتراوح من 6.35:1 الى 13:1 بدون أي تأثير على جودة الصورة المستخدمة في التشخيص الطبي.

1. INTRODUCTION

Nowadays a large number of medical images are generated from hospitals and medical centers with sophisticated image acquisition devices such as computed tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound (US), X-Ray diffraction, Electrocardiogram (ECG), Nuclear Medicine (NM), Computed Radiography (CR), Digital Subtraction Angiography (DSA), and Positron Emission tomography (PET). The movement towards digital images in radiology presents the problem of how to conveniently and economically store, retrieve and transmit volumes of digital images. Thus digital image data compression is necessary in order to reduce the storage of medical images and solve practical limitations of transmission bandwidth. However, as the number of digital modalities increases, the demand for an efficient medical image compression is increasing. Digital image data compression consists of two types of compression technique: error-free and irreversible. Error-free image compression is desired; however, present techniques can only achieve compression ratio from 1.5:1 to 3:1, depending upon the image characteristics. Irreversible image compression can achieve a much higher compression ratio;

however, the image reconstructed from the compressed data shows some difference from the original image. [1]

The choice of the compression method, lossy or lossless, depends on the application. For example, in applications dealing with speech signals and video television images, where some loss of information can be tolerated, lossy compression methods can be used. On the other hand in a wide range of medical applications and under special circumstances such as disease diagnostic, the loss of information is unacceptable; hence medical images are required to be at high resolution possible. Thus, rather than lossy compression with relatively high compression ratio, mathematical lossless compression methods are favored in this field. [2]

In this paper a new coding algorithm for medical images is presented. This algorithm is near lossless and based on pixel redundancy reduction using only two matrices for coding and decoding processes without affecting the quality of the resultant reconstructed image.

2. BACKGROUND

Compression is the process of storing or packing data in a format that requires less space than the initial file. Compression takes an input X and generates a representation X_c that hopefully requires fewer bits. There is a reconstruction algorithm that operates on the compressed representation X_c to generate the reconstruction Y and the performance of the algorithm depends on the type of the compression technique.

Table 1 illustrates the need for sufficient storage space, large transmission bandwidth and long transmission time for image, audio and video data. At the present state of technology, the only solution is to compress

multimedia data before its storage and transmission, and decompress it at the receiver for play back.

Table 1: Memory Space, Transmission Bandwidth and Transmission Time Requirements for Uncompressed Multimedia Data Files [3]

| Multimedia Data | Size | Resolution Bit/Pixel | Uncompressed Size (Bytes) | Transmission Bandwidth | Transmission Time |
|---------------------------------|--------------------------|-----------------------------|----------------------------------|-------------------------------|--------------------------|
| A paper of text | 11"x8.5" | Varying resolution | 4-8 KB | 32-64 Kb/page | 1.1 -2.2 sec |
| Telephone quality speech | 10 sec | 8 | 80 KB | 64 Kb/sec | 22.2 sec |
| Grayscale Image | 512x512 | 8 | 262 KB | 2.1 Mb/image | 1 min 13 sec |
| Color Image | 512x512 | 24 | 786 KB | 6.29 Mb/image | 3 min 39 sec |
| Medical Image | 2048x1680 | 12 | 5.16 MB | 41.3 Mb/image | 23 min 54 sec |
| Full-motion video | 640 x 480 (30 fr/sec) | 24 | 1.66 GB | 221 Mb/image | 5 days 8 hrs |

In teleradiology applications, medical image compression is essential despite rapid growth in digital communication systems performance, mass storage and processors speed. The requirement for data storage capacity and bandwidth continue to exceed the capability of available technologies.

A radiologist would need to review personally all the medical images at a computer workstation to make sure that all possible information that might be clinically important is reviewed at all combinations of window level settings.

Table 2 shows that data files of images would become much larger and consequently retrieval of images from archives will be slow. So, without image compression, digital imaging would be more expensive, less practical, and less attractive for the advantages it offers. Either transmission time would be much longer or telecommunication equipment and line charges would be more expensive .[4] Therefore, teleradiology and telemedicine would in many situations be impractical, unacceptably slow and expensive. [5]

Table 2: Sizes and Storage Requirement for Radiological Images [6]

| <i>Modality</i> | <i>Image size (pixels)</i> | <i>Resolution (bits/pixel)</i> | <i>Average images per exam</i> | <i>Average storage requirement (MB)</i> |
|-----------------|----------------------------|--------------------------------|--------------------------------|---|
| CT | 512x512 | 12 | 30 | 15 |
| MRI | 256x256 | 12 | 50 | 6.5 |
| DSA | 1000x1000 | 8 | 20 | 20 |
| US | 512x512 | 6 | 36 | 9 |
| NM | 128x128 | 8 | 26 | 0.4 |
| CR | 2000x2000 | 10 | 4 | 32 |
| Digitized film | 4000x4000 | 12 | 4 | 128 |

3. MATERIALS AND METHODS

The proposed algorithm takes the advantage of still image characteristics and human visual system sensitivity. A typical still image contains a large amount of redundancy in many areas, where adjacent pixels have almost the same values [7] , [8]. Whereas the human visual system (HVS) essentially can accommodate that each pixel value of an image is changed by a certain amount (limit) without making any perceptible difference to the image quality. This limit is called the Just Noticeable Distortion (JND) level. [9]

Our algorithm is based on those facts by forming only two matrices, binary matrix and grayscale matrix. It has been tested on a set of MRI images. The main steps of the proposed algorithm are as follows:

STEP1: Read the original image matrix [OR].

STEP2: Construct the binary matrix [BM] and grayscale matrix [GSM] as indicated in the next steps.

STEP3: Compare each pixel in the matrix [OR] with the previous pixel in the same matrix as indicated in figure 1.

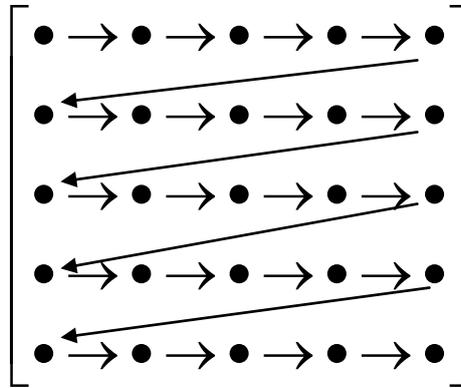


Figure 1. Original Image Pixels Comparison

STEP4: The binary matrix elements are calculated as follows:

$$[BM]_{i,j} = \begin{cases} 0 & \text{if } |[OR]_{i,j} - [OR]_{i,j+1}| \leq n \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

where: $n = 0, 2, 4, 8, 16, 18, \dots, 28$

$$i = 0, 1, 2 \dots M$$

$$j = 0, 1, 2 \dots N$$

M, N is size of the original image

STEP5: First element in [GSM] is set to be equal to the value of the first pixel of [OR]

STEP6: The rest of the elements of [GSM] are calculated as follows:

$$[GSM]_k = \begin{cases} nul & \text{if } |[OR]_{i,j} - [OR]_{i,j+1}| \leq n \\ [OR]_{i,j} & \text{otherwise} \end{cases} \quad (2)$$

where: $k= 0,1,2,\dots, l$

l is size of the grayscale matrix [GSM]

STEP7: The original image can be reconstructed as follows:

$$[rec_img]_{i,j} = \begin{cases} [GSM]_k & \text{if } [BM]_{i,j} = 0 \\ [GSM]_{k+1} & \text{if } [BM]_{i,j} = 1 \end{cases} \quad (3)$$

The performance of the proposed algorithm is measured by compression ratio achieved which is defined as follows:

$$(CR) = \frac{\text{original file size}}{\text{compressed file size}} \quad (4)$$

The quality of the compressed image is measured using Peak Signal-to-Noise Ratio (PSNR), based on the Mean Square Error (MSE) of the reconstructed image. The formula for PSNR calculation is given by [5]:

$$PSNR = 20 \log \left(\frac{2^B - 1}{MSE} \right) \text{dB} \quad (5)$$

Where B is the bit depth of the image. For an 8-bit image, the PSNR is computed

by[5]:

$$PSNR = 10 \log \left(\frac{(255)^2}{MSE} \right) \text{dB} \quad (6)$$

MSE is the Mean Square Error and it can be calculated using the following formula [5]:

$$MSE = \frac{1}{NM} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \left[|f(i, j) - f^*(i, j)|^2 \right] \quad (7)$$

where:

M, N is the image size

$f(i, j)$ is the original image

$f^*(i, j)$ is the compressed image

4. RESULTS AND DISCUSSION

The proposed algorithm was implemented using MATLAB [10]. The results are obtained from testing a sample of sixteen original MRI images. The original images are grayscale images of 8 bits per pixel, as shown in figure 2. The compression ratio obtained using the proposed technique at different n values is summarized in table 3. Samples of the reconstructed images (Image case No.1) are shown in figure 3 and the calculated values of the **CR** and **PSNR** are explained in table 4.

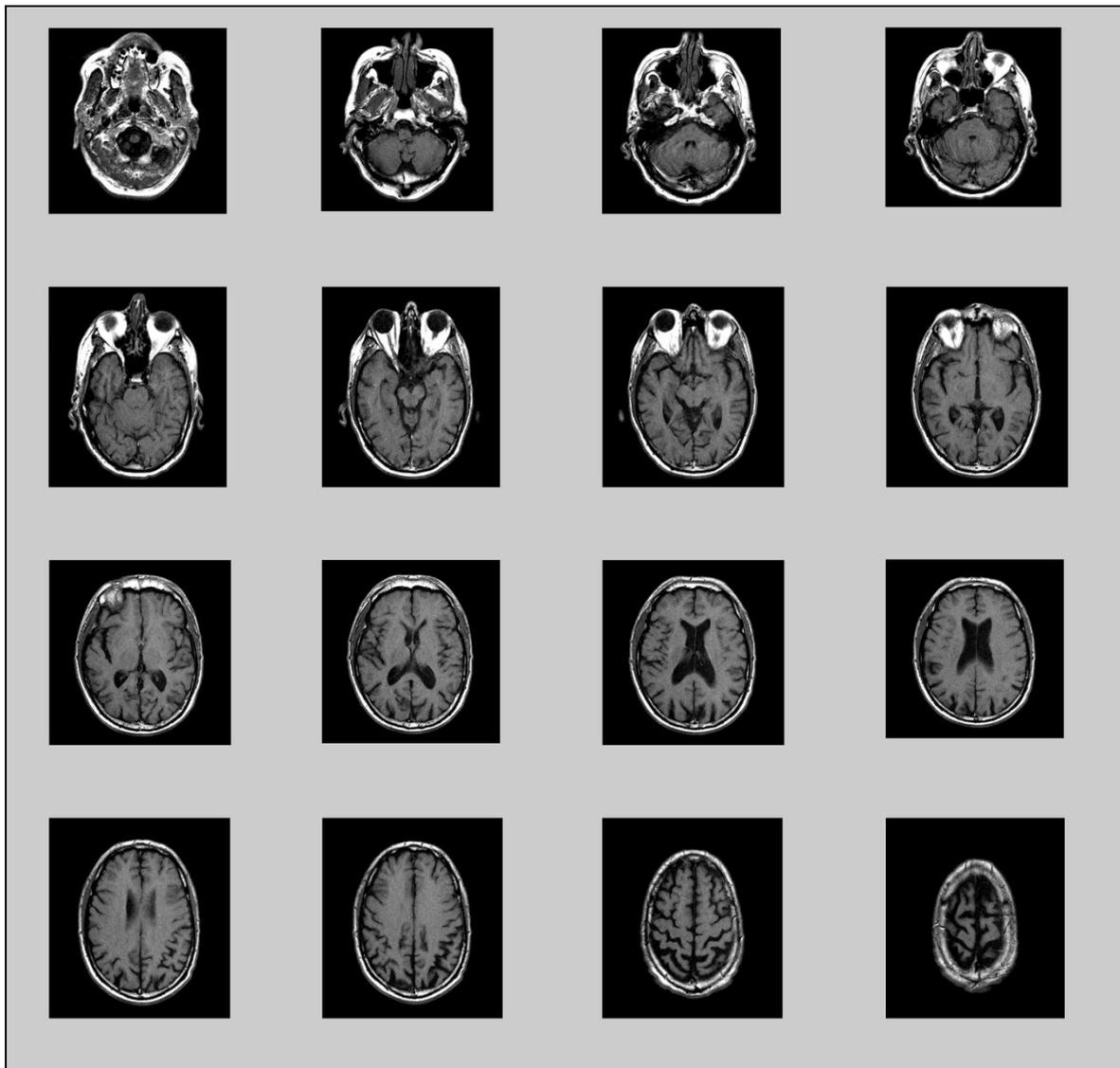


Figure 2 . Original Test Images

From table 3, it can be seen that the performance of the proposed algorithm can be increased whenever the value of n is increased but up to a certain limit (JND level), which is in our case ($n=16$). This limit is assigned by specialists from National University of Malaysia Medical Center (*UKM-MC*), who are involved in evaluating our results, because if n is more than 16, distortion will easily be detected and the quality of the reconstructed image will be affected as indicated in figure 3.

Table 3. The Performance of the Proposed Algorithm

| <i>Image #</i> | <i>Compression Ratio achieved by the Proposed Algorithm</i> | | | | |
|----------------|---|------------|------------|------------|-------------|
| | <i>n=0</i> | <i>n=2</i> | <i>n=4</i> | <i>n=8</i> | <i>n=16</i> |
| 1 | 2.32 | 4.57 | 4.76 | 5.24 | 6.35 |
| 2 | 2.56 | 5.04 | 5.31 | 5.97 | 7.55 |
| 3 | 2.51 | 4.93 | 5.17 | 5.74 | 7.07 |
| 4 | 2.40 | 4.77 | 5.03 | 5.64 | 7.07 |
| 5 | 2.35 | 4.63 | 4.92 | 5.59 | 7.28 |
| 6 | 2.26 | 4.54 | 4.85 | 5.55 | 7.35 |
| 7 | 2.24 | 4.55 | 4.86 | 5.59 | 7.50 |
| 8 | 2.20 | 4.46 | 4.79 | 5.58 | 7.60 |
| 9 | 2.19 | 4.48 | 4.81 | 5.65 | 7.86 |
| 10 | 2.21 | 4.45 | 4.80 | 5.70 | 7.92 |
| 11 | 2.25 | 4.61 | 4.99 | 5.93 | 8.54 |
| 12 | 2.33 | 4.73 | 5.17 | 6.23 | 9.23 |
| 13 | 2.41 | 4.90 | 5.33 | 6.40 | 9.36 |
| 14 | 2.52 | 5.14 | 5.55 | 6.55 | 9.23 |
| 15 | 2.84 | 6.13 | 6.55 | 7.53 | 9.83 |
| 16 | 3.07 | 8.15 | 8.62 | 9.89 | 13.04 |

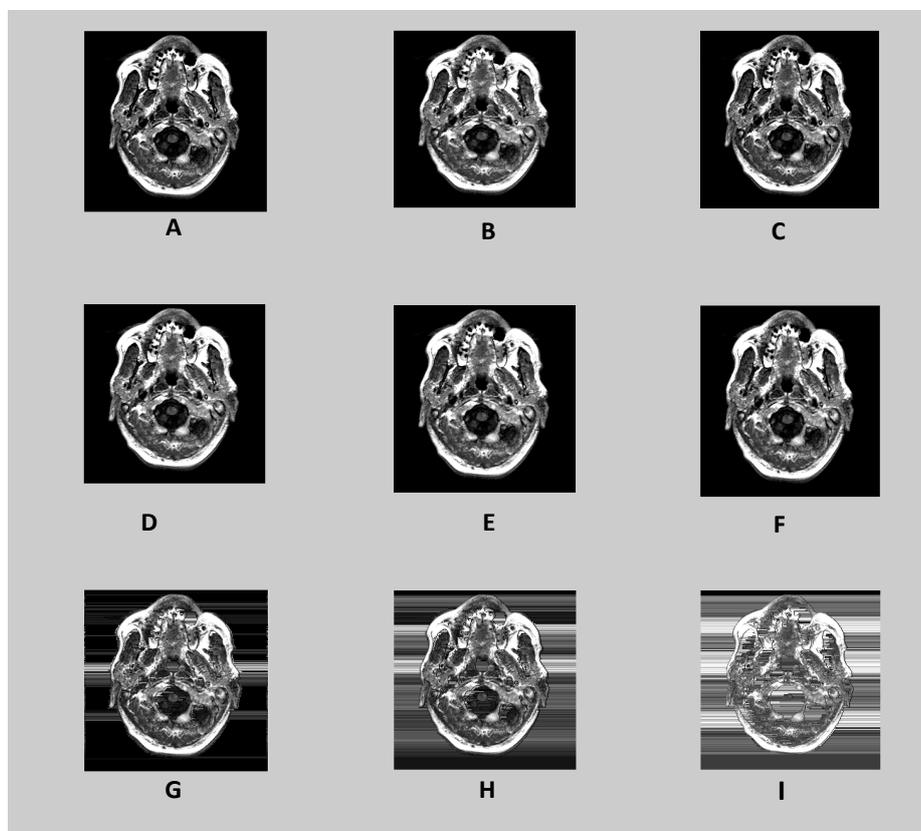


Figure 3 Proposed Algorithm Applied on the First Image of Test Images

Table 4 The CR and PSNR of the Image no.1

| <i>Image</i> | <i>n Value</i> | <i>CR</i> | <i>PSNR (dB)</i> |
|--------------|----------------|-----------|------------------|
| A | 0 | 2.32 | 39.60 |
| B | 2 | 4.57 | 38.95 |
| C | 4 | 4.76 | 37.67 |
| D | 8 | 5.24 | 35.82 |
| E | 16 | 6.35 | 34.22 |
| F | 18 | 7.00 | 32.97 |
| G | 24 | 8.44 | 31.42 |
| H | 28 | 9.33 | 30.58 |
| I | 32 | 10.21 | 29.49 |

5. CONCLUSION

In this paper an efficient, simple near lossless image coding technique is proposed with a remarkable compression ratio and greatly reduced computation load while keeping low complexity compared with other methods. It is very useful for medical images where disease diagnostic requires images to be at as high resolution as possible. It can also be useful for teleradiology and archiving purposes.

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