International Journal of Electrical and Electronics Engineers
Volume 15, Issue No. 01, Jan-June 2023
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

A FAST FRACTAL BASED COMPRESSION ON MRIIMAGES

MR. G. MALLIKARJUNA[1], K. ROOHI[2], CH. JAGADEESH[3], A. DALLISRI[4], A. SAIDARO[5]

Aoss.Prof[1], Students[2-5], Tirumala Engineering College, Narasaraopet, Andhra Pradesh, India.

ABSTRACT

Magnetic resonance imaging (MRI), which assists doctors in determining clinical staging and expected surgical range, has high medical value. A large number of MRI images require a large amount of storage space and the transmission bandwidth of the PACS system in offline storage and remote diagnosis. Therefore, high- quality compression of MRI images is very research-oriented. Current compression methods for MRI images with high compression ratio cause loss of information on lesions, leading to misdiagnosis; compression methods for MRI images with low compression ratio does not achieve the desired effect. Therefore, a fast fractal-based compression algorithm for MRI images is proposed in this paper. First, three-dimensional (3D) MRI images are converted into a two-dimensional (2D) image sequence, which facilitates the image sequence based on the fractal compression method. Then, range and domain blocks are classified according to the inherent spatiotemporal similarity of 3D objects. And then by using quadtree decomposition method we will compress the Image with the help of Huffman encoding and decoding algorithms, and the we apply residual compensation technique for finding the ROI region.

1. INTRODUCTION

Medical imaging has become one of the most active and rapidly evolving fields in medical research and clinical diagnosis. Medical images display the internal structure of the human body in an intuitive form, providing clinicians with intuitive and accurate basic information on anatomy, pathology and function. Typical imaging modalities include magnetic resonance imaging (MRI), computer-assisted tomography (CT), ultrasound (US), computer-assisted X-ray (CR), digital subtraction angiography (DSA), et al. With continuous advancement of medical imaging technology, especially the resolution of imaging devices, the amount of medical image data will continue to grow. Existing bandwidth conditions are difficult to meet the real-time transmission requirements of large data volumes. To meet effective storage and transmission of medical images, it is not only necessary to expand storage space and transmission bandwidth, but also to study how to efficiently compress medical data. Therefore, it is necessary to implement effective compression of various medical images using an image compression algorithm.

Medical image compression methods are generally classified into lossless compression and lossy compression. Lossless compression provides medical diagnostics with image information of the same quality as the original image. However, the compression ratio of lossless compression is usually low, which is difficult to meet the actual transmission requirements of medical images. Lossy compression provides a higher compression ratio by losing some information. Increase in compression inevitably brings a certain degree of degradation to medical images. In the future of telemedicine applications, lossless compression will be difficult to provide a low bit rate required for image transmission, while relying on lossy compression to achieve real-time transmission of images. At present, lossy compression technology for medical images has become a research hotspot at domestic and international, and its research goal is to improve the reconstruction quality of images as much as possible under a given coderate.

MRI medical images contain rich temporal and spatial correlations. As shown in Fig. 1, three similar image blocks 1, 2, and 3 are respectively derived from three adjacent MRI medical image slices. The spatiotemporal correlation means that in a MRI image slice, its adjacent fields of a certain pixel (region) in a layer of image (several layers before and after) have a strong similar relationship with the pixel (region). This spatiotemporal correlation makes a large amount of (local) self-similar information contained in MRI images. Therefore, it is considered to compress this type of medical image using the fractal compression idea. Fractal image compression is based on Iterated Function System (IFS), omitting the image content, and only retaining self-similarity parameters of the local image content to complete data compression. It has advantages of high compression ratio, reconstruction at any scale, and fast decoding. However, traditional fractal compression algorithm fails to fully consider the spatiotemporal relationship of MRI images, resulting in inefficient and poor results. Therefore, a fast fractal-based compression algorithm for MRI images is proposed in this paper.

In this study, our contribution is to apply sequence image-based fractal compression method to compress three-dimensional MRI images. Besides, to get better performance of compression, we proposed two improvements. First, range blocks and domain blocks are classified according to the spatiotemporal similarity feature. A range block only needs to search for the optimal matching block in a certain type of domain block. Compression process is accelerated by reducing the capacity of matching pool. Second, the residual compensation mechanism is introduced to achieve approximate lossless compression of MRI images. The experimental results show that the proposed method improves compression efficiency under the premise of ensuring image quality of MRI.

2. LITERATURE REVIEW

Bruckmann and A. Uhl, ‘‘Selective medical image compression techniques for telemedical and archiving applications. In this the selective Image Compression is a compression technique where explicitly defined regions of interest (ROI) are compressed in a lossless way whereas Image regions containing unimportant information are compressed in a lossy manner. Such techniques are of great interest in telemedicine or medical imaging applications with large storage requirements. It introduce and compare techniques with different functionalities. Moreover, we investigate the impact of using wavelet transforms and JPEG as underlying lossy compression algorithm.

P. G. Tahoces, J. R. Varela, M. J. Lado, and M. Souto, ‘‘Image compression: Maxshift ROI encoding options in JPEG2000,’’ Comput. Vis. Image Understand., vol. 109, pp. 139–145, Feb. 2008. Compression can improve the performance of the digital systems by reducing the time and cost in image storage and transmission without significant reduction of the immense quality Furthermore the JPEG 2000 has emerged as the new state of the art standard for image compression The selective coefficient makes shift coding method is proposed This technique

International Journal of Electrical and Electronics Engineers
Volume 15, Issue No. 01, Jan-June 2023
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

implemented over region of interest is based on shifting the wavelet coefficients that belong to defence substance depending on the coefficients related to the original image This method allows codification of multiple roses at various degrees of interest.

P. E. Sophia and J. Anitha, ‘‘Implementation of region based medical image compression for telemedicine application,’’ in Proc. IEEE Int. Conf. Comput. Intell. Comput. Res., Dec. 2014, pp. 1–4. Medical images are rich in radiological information and file sizes associated with also large medical images such as MRI produce human body pictures in digital form And they produce excessive amount of data So compression is necessary for stories and transmission purpose Image compression enhancer performance of any digital system by reducing the time and cost without without reduction in immense quality the result of three different classical algorithms with and without ROI are compared the results are reported.

3. PROPOSED METHOD

Fast fractal based compression on MRI Images

Fractal MRI Image compression based on sequence Image: Three-dimensional MRI image is essentially a data cube that adds third-dimensional information to a common two dimensional image. For the form in which three- dimensional image has a data cube, we convert three- dimensional MRI image into two-dimensional sequence images for compression. First, the image to be compressed is divided into a series of fixed size N × N pixel sub-blocks. They do not overlap each other and cover the entire image, which is called a range block (R block). Subsequently, the image to be encoded is again divided into domain blocks (D blocks) having a size of 2N × 2N, and D blocks may overlap. Before the encoding, D block is averaged by the four neighboring pixels, and its size is reduced to be the same as the size of R block. The averaged sampled D block is subjected to eight kinds of equidistant transformations, and the transformed whole constitutes codebook • . For each R block, it is necessary to find its best matching D block in the codebook • . Each R block is then approximated by the luminance transform of its best matching block D ∈

• , that is R = s • D + o • 1. Where 1 is a unit matrix of N

× N, and s, o are the contrast and brightness adjustment factors of D block, respectively. Fractal MRI image compression process based on sequence of image.

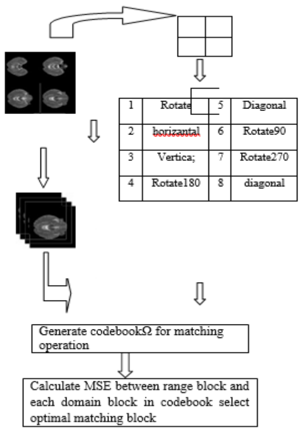

Fig:Image compression based on sequence of MRI images

International Journal of Electrical and Electronics Engineers
Volume 15, Issue No. 01, Jan-June 2023
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

Again divided into domain blocks (D blocks) having a size of 2N × 2N, and D blocks may overlap. Before the encoding, D block is averaged by the four neighboring pixels, and its size is reduced to be the same as the size of R block. The averaged sampled D block is subjected to eight kinds of equidistant transformations, and the transformed whole constitutes codebook • . For each R block, it is necessary to find its best matching D block in the codebook • . Each R block is then approximated by the luminance transform of its best matching block D ∈ • , that is R = s • D + o • 1. Where 1 is a unit matrix of N × N, and s, o are the contrast and brightness adjustment factors of D block, respectively. Fractal MRI image compression process based on sequence image is shown

The following are specific steps of fractal MRI imagecompression algorithm based on sequence image:

Input: MRI image F of size M × M. Output: Fractal encoded file dx, dy, t,s, o.

Step 1: Perform fixed block partitioning on MRI image F,and divide it into a range block (R block) whose size is N ×N but does not overlap each other.

Step 2: The 2N × 2N intercepting window is moved in horizontal and vertical directions of the image F by a step size δ, and the intercepted block after each movement constitutes a domain block (D block).

Step 3: Perform average sampling and eight equidistanttransformations on all D blocks to form a codebook .

Step 4: For an arbitrary range block Ri , find the bestmatching block D 0 j that satisfies Eq.1 in codebook

QUADTREE DECOMPOSITION: Fast Fractal Geometry has become an important branch of image compression and covering many branches of science and engineering. The main problem is that the fractal encoding is taking too much time. Many approaches to reduce the encoding time has bad affection on the image quality after iteration, therefore the hybrid encoding divides a square image into four equal sized square blocks, and then tests each block to see if meets some criterion of homogeneity. If a block meets criterion it is not divided any further, and the test criterion isapplied to those blocks. This process is repeated iteratively until each block meets the criterion.

HUFFMAN CODING: The Huffman encoding algorithm starts by constructing alist of all the alphabet symbols in descending order of their probabilities. It then constructs, from the bottom up, a binary tree with a symbol at every leaf. This is done in steps, where at each step two symbols with the smallest probabilities are selected, added to the top of the partial tree, deleted from the list, and replaced with an auxiliary symbol representing the two original symbols. When the list is reduced to just one auxiliary symbol, the tree is complete. The tree is then traversed to determine the code words of the symbols.

HUFFMAN DECODING: At the start of the compression of a data file the encoder has to determine the codes It does that based on the probabilities of frequencies of occurrence of the symbols The probabilities or frequencies have to be written as a side information on the output Huffman decoder will be able to decompress the data this is easy because the frequencies are integer and the probabilities can be written as scaled in teasersIt normally adds just a few 100 bytes to the output It is also possible to write the variable length courts themselves on the output But thismay be awkward because the codes have different sizes but this may require more space than just the frequencies in any case the decoder must know what is at the start of the completed file. Read it and construct the Huffman tree for the alphabet The algorithm for decoding is simple Start at the root andread

International Journal of Electrical and Electronics Engineers
Volume 15, Issue No. 01, Jan-June 2023
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

the first bit of the input If it is zero follow the bottom edge of the tree If it is one follow the top edge Read the n,ext bit and move another edge to what the leaves of the tree when the decoder arrives at a leaf it finds Zeta original uncompressed symbol And that codeis emitted by the decoder.

RESIDUAL COMPENSATION MECHANISM: Residual compensation mechanism is optimal, which is used for comparison between original image and reconstructed image by finding the ROI region and Huffman coding. This gives the difference between proposed method and traditional method.

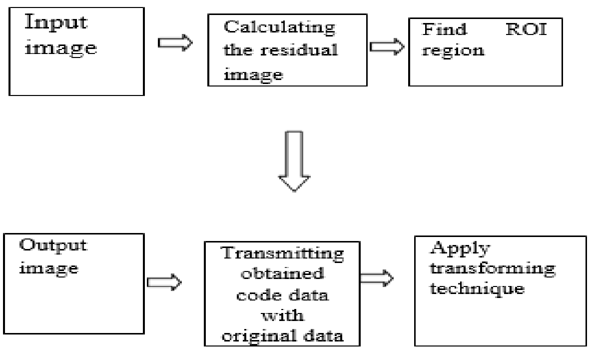

Fig: Residual compensation method

From the residual compensation method we will find the ROI part of the region and we will highlight the tumour part of the image which is used to compress.

```
Time taken for compression = 0.476063 seconds
compression ratio= 12.649296
Time taken for Decompression = 2.769399 seconds
```

Fig: Output for time taken to compress the Image

So from the above the time taken from compression is seconds, and the compression ratio is 12.6 after for obtaining our data image we have to decompress the image in order to get the original image and the time taken for decompression is 2.7.

3. CONCLUSION

We propose a fractal based compression on MRI Images by using quadtree decomposition with the help of Huffman encoding and decoding algorithm, Finally we applied residual compensation mechanism method for finding the ROI region and highlight the tumour part in the image.

REFERENCES

[1] Bruckmann and A. Uhl, ‘‘Selective medical image compression techniques for telemedical and archiving applications,’’ Comput. Biol. Med., vol. 30, pp. 153–169, 2000.

[2] P. G. Tahoces, J. R. Varela, M. J. Lado, and M. Souto, ‘‘Image compression: Maxshift ROI encoding options in JPEG2000,’’ Comput. Vis. Image Understand., vol. 109, pp. 139–145, Feb. 2008.

[3] Y.-D. Zhang, Z. Dong, L. Wu, and S. Wang, ‘‘A hybrid method for MRI brain image classification,’’ Expert Syst. Appl., vol. 38, pp. 10049–10053, Aug. 2011.

[4] S. M. Hosseini and A.-R. Naghsh-Nilchi, ‘‘Medical ultrasound image compression using contextual vector

International Journal of Electrical and Electronics Engineers
Volume 15, Issue No. 01, Jan-June 2023
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

quantization,'' Comput. Biol.Med., vol. 42, pp. 743–750, Jul. 2012.

[5] P. E. Sophia and J. Anitha, ''Implementation ofregion based medical image compression for telemedicine application,'' in Proc. IEEEInt. Conf. Comput. Intell. Comput. Res., Dec. 2014, pp. 1–4.

[6] K. C. Pathak and J. N. Sarvaiya, ''Lossless medical image compression using transform domain adaptive prediction for telemedicine,'' in Proc. Int. Conf. Wireless Commun., Signal Process. Netw. (WiSPNET), Mar. 2017, pp. 1026–1031.

[7] U. V. Selvi and R. Nadarajan, ''CT and MRI image compression using wavelet-based contourlet transform and binary arraytechnique,'' J. Real-Time Image Process., vol. 13, no. 2, pp. 261–272, 2017.

[8] C. P. Devadoss and B. Sankaragomathi, ''Near lossless medical image compression using block BWT–MTF and hybrid fractal compression techniques,'' Cluster Computing, 2018.

[9] X. Jiang, ''Isolated Chinese sign language recognition using gray-level co-occurrence matrix and parameter-optimized medium Gaussian support vector machine,'' in Proc. 7th Int. Conf. Frontiers Intell. Comput., Theory Appl. (FICTA), 2019, pp. 1–10.