An Improved Irreversible Fractal Scheme for Medical Image Compression

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Abstract. In this paper, an improved fractal image compression (FIC) based on peer adjacent scheme and domain classification was proposed. The proposed method has low computation cost since it contains no search operations, thus becoming fast irreversible fractal scheme. Comprehensive experiments on a standard test image and several types of digital radiology images revealed that the proposed method is competitive when compared to established quadtree-based FIC techniques. The novelty of the proposed method lies in the use of this improved domain classification and mapping strategy for accurate and more precise FIC encoding. The empirical result of standard test image suggests that the proposed method is more competitive compared to the established schemes and achieves better performance in terms the peak signal-to-noise ratio (PSNR) and compression time averaging at 27.27 dB and 6.88 s, respectively. Also, the proposed method obtains an efficient compression ratio with 16.13 compared to others. Additionally, experiments involving various medical image modalities confirmed the superiority of the proposed method for practical applications of medical image compression.

1. Introduction

Nowadays, almost all hospitals rely on digital medical imaging as an important and robust part in controlling the full chain of patient care. A completely digital workflow with improvements in medical imaging scanners technology and the importance of volumetric digital image datasets have all expressed the need for more efficient compression technique. Some of the quality attributes required when compressing medical data include high compression ratio and the ability to decode the compressed data at various resolutions. For medical images, compression methods with high compression ratio cause loss of important information on lesions, thus resulting in misdiagnosis. Meanwhile, the low compression ratio does not deliver the desired outcome. As fractal strategy contributes a lossy image compression and yields higher compression, it is applied to compress medical images. In archiving a high compression ratio, FIC employed the excess of self-similarity at various layers and represented the original image in a vector form. Thus, very high data compression is produced compared to other established lossy methods. Although this technique is not accepted as a standard compression technique because of the high computational complexity of the encoding phase [1]. Further, a faster and higher compression ratio is needed to compress and decrease the storage
space as medical images being expansive. Therefore, an improved irreversible fractal scheme for medical images is proposed in this paper.

But, in compressing medical images using FIC, there is not much of research work published yet. Bhavani et al. [2] recommended two strategies to facilitate the FIC search. They are (i) domain range block separation by variance, and (ii) domain range block grouping by a self-organizing neural network-based machine learning technique. Their strategies allow a significant reduction of encoding time and also improvement in the compression ratio. But, the use of threshold value to decides the size of the domain pool leads to a try-and-error way. Meanwhile, Khalili et al. [3] suggested an image segmentation as a trade-off between computational cost and compression accuracy. In this case, the original image is partitioned into the background (whose information is not significant) and the region-of-interest (ROI). Then the different range size is assigned for each segment of the image where a large range size for background and the small range size for ROI to avoid loss of information.

Sheeba and Rahiman [4] proposed a method using the Cayley table to predict the transformation part in FIC. To further decrease the number of computations in the encoding process, the score value is measured exclusively for domain and range blocks. An advantage of this technique is that the reduction of encoding time with a better peak signal-to-noise ratio (PSNR) value compared to other established fractal coding schemes. Recently, Menassel et al. [5] improved the FIC by incorporating Bat inspired algorithm as a naturally inspired metaheuristic. Compared with other methods, Menassels’s algorithm offers better results in compress image quality, but, suffers a long compressing time and lower compression ratio compared to others.

One of a continuous FIC area of research is in reducing the encoding complexity. For example, the work of Thomas and Deravi [6] combines range blocks and makes them more adaptive with image content by using the region-growing method to reduce the massive encoding time. Cardinal [7] proposes an associated strategy based on a geometric partition of the greyscale image block feature space. The comparisons with other established methods give an important change in speed with an acceptable quality of the compressed image. An adaptive search scheme to speed up and lessen the fractal encoding complexity is performed by Chong and Pi [8]. The scheme work by discarding the unfit domain blocks. In another manner, He et al. [9] have proposed a method to bypass the unnecessary search in block matching by utilising the one-norm of the normalized block. In order to improve the search quality, some other researchers were presented novel concepts like the encoding through special image features [10] and the Fourier transform [11]. Most of the current approaches are based on limiting the search space by thresholding.

The standard FIC mapping process between domain and range to get the contractivity coefficients is done by searching for equivalent range with all potential domains in the domain pool. There is no need for a domain pool to include all possible domain blocks, only the high-variance blocks would be enough [12]. The high-variance domain blocks have adequate ability to be mapped to all range blocks with a small enough error. Hence, the low-variance domain blocks were removed from the domain pool and only a small domain pool is used [13]. This process is complex and involved a large number of computations. So, in an attempt to overcome this problem, a concept of peer adjacent and domain classification was proposed.

2. Proposed method
The flow chart in Figure 1 summarizes the improved FIC algorithm. Briefly, the process starts by partitioning the image into range and domain blocks using a quadtree partitioning approach. Second, the domain block is selected and grouped using the proposed peer adjacent scheme and the Pearson correlation coefficient (PCC) algorithm [14]. Third, the mapping process between domain and range block is done by selecting range blocks from partitioning list and domain block from the classified domain list. Fourth, all mapped domain and range blocks are being fit each other using affine transformation and distortion measure. If they are fit within error tolerance, then the domain block will be chosen as the most similar domain for the range block. Else, it will continue mapping with other domain blocks and the fitting process is repeated. Finally, the mapping process will end until there are no more range blocks to be mapped and the coefficient for each range block will be saved as a fractal codebook.
2.1. Peer Adjacent Domain
By utilizing the peer adjacent mapping method, the improvement in the FIC domain selection is done, without sacrificing the image quality and storage space of the compressed image. It lets costly process replacement of conventional FIC mapping with peer adjacent schemes. Basically, the mapping process can be simplified by restricting the range to compare with its peer adjacent domain, instead of a group of domains. Figure 2 illustrates the concept of peer adjacent mapping for domain and range block, where a group of four ranges are mapped to a common peer adjacent domain block.

Figure 1. Flow chart of the improved encoding FIC algorithm.

Figure 2. Peer adjacent mapping for domain and range block.
From Figure 2, the input image is divided into square blocks that do not overlap each other. Domain block size is twice the range block. The mapping process begins by range blocks, \( R_{nm} \) in the lower hierarchy searching for a particular domain block, \( D_m \) in the upper hierarchy. The process is repeated for all existing hierarchies in the input image. Consequently, the amount of calculation can be reduced, resulting in faster encoding time. The method also helps in reducing the fractal codebook size, because the domain block is shared between all four range blocks. Consequently, only one domain block location is saved into the codebook and the compression ratio can be enhanced indirectly.

2.2. Domain Classification
In order to preserve a high quality compressed image, the need for an extra procedure in classifying the domain blocks is a must. In this step, the peer adjacent domain will be classified by using the PCC algorithm. A linear dependency between two variables; for example, A and B can be measured using PCC. It has a value between +1 and −1, where +1 and -1 represent a positive and negative linear correlation, respectively, and 0 value indicates a zero-order correlation. If each variable has \( N \) scalar observations, then the PCC is defined as:

\[
p(A, B) = \frac{1}{N - 1} \sum_{i=1}^{N} \left( \frac{A_i - \mu_A}{\sigma_A} \right) \left( \frac{B_i - \mu_B}{\sigma_B} \right)
\]

where \( \sigma \) and \( \mu \) are the standard deviation and mean, respectively. In this procedure, the PCC is used to create three sets of domain labels. The group labels are based on the degree of strength of relationships between domains. In this paper, the first group is classified for a domain that has PCC less or equal to 0.1, the second group with PCC is greater than 0.1 and less or equal to 0.3 and the rest of the domain will form the third group.

2.3. Test Images and Quality Indices
The standard image Lena (256 × 256-pixel dimension) is used in comparing the proposed method with other established quadtree-based FIC methods. The efficiency of the proposed method in compressing medical images is evaluated using various types of digital radiology images which are mammography, computed tomography (CT) and magnetic resonance imaging (MRI) images from The Cancer Imaging Archive (TCIA) [15] and computed radiography (CR) from JSRT database [16]. Each imaging modality has a different size from the smallest image of MRI (256 × 256-pixel dimensions) up to the largest one of mammography image with typically 4096 × 4096 pixels. In total there are 40 test images used to evaluate the proposed method in compressing medical images.

In this paper, PSNR, runtime and compression ratio (C\(_{\text{ratio}}\)) has been used as quality measures. In general, PSNR represents signal and distorting noise strengths in influencing the quality of its representation. It can be expressed by mathematical representations as follows [17]:

\[
PSNR = 10 \log_{10} \left[ \frac{K^2}{MSE} \right]
\]

where \( K \) is the maximum fluctuation in the input images. Meanwhile the MSE is defined as:

\[
MSE = \frac{\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (W(m,n) - \hat{W}(m,n))^2}{M \times N}
\]

where \( W \) and \( \hat{W} \) are respectively the original and reconstructed images, each of size \( M \times N \). PSNR is the most widely used objective image quality and is indicated in the logarithmic decibel (dB) scale; due to the majority of image signals belong to a very broad range of dynamics. The value of PSNR is
measured by the higher the PSNR, the better the image quality assessed. For the $C_{\text{ratio}}$, it is defined as the ratio between the size of the original and compressed images. Mathematically:

$$C_{\text{ratio}} = \frac{\text{original}}{\text{compressed}}$$  \hspace{1cm} (4)

3. Results and Discussion
The performance of the proposed method was discussed in this section. An experiment and simulation is conducted using MATLAB® to measure its effectiveness on the compression of greyscale test image Lena with established quadtree-based FIC methods. The performance is assessed based on image quality, compression time (s) and $C_{\text{ratio}}$.

3.1. Standard Test Image
Figure 3 shows the results of image compressing quality, compression time and $C_{\text{ratio}}$ for the proposed method compared to the established method by Gupta et al. [18], Xing-Yuan et al. [19] and Wang and Zhang [20]. The reconstructed Lena image using the proposed method has the best image fidelity comparing to others method since it obtained the highest PSNR.

Close examination of Figure 3 reveals that the proposed method attained the best compressing quality with highest PSNR value compared to others. Plus, the proposed method is faster than Wang and Zhang and Gupta et al.’s methods. This is due to the Gupta et al.’s method is using the nearest-neighbour technique in various frequency domains while our method employed no search scheme in the domain mapping process. Meanwhile, Wang and Zhang’s method applied a learning scheme for domain classification, thus recorded the slowest computational time. For the compression ratio, the proposed method obtains an efficient result with 16.13. Higher $C_{\text{ratio}}$ implies that the compressed
image size is much smaller than its original image. As a summary, it proves that our method not only produced an exceptional compressed image quality but also accelerated the compression procedure with an acceptable compression ratio.

3.2. Medical Images

As stated in the previous section, the standard test image result shows that our proposed method performs better in terms of compressed image quality and speed, but slightly lower in $C_{\text{ratio}}$. In order to measure the proposed method in compressing medical images, the quantitative study was executed using various types of digital radiology images. The quality measures in terms of PSNR, compression time and $C_{\text{ratio}}$ have been used and the results are tabulated in Table 1. Three different range sizes with minimum and maximum value have been set for different image modalities, where range (2,4) for MRI and CT images, range (4,8) is used to compressed the CR images, and range (8,16) is used for mammography images. The reason is to vary the experiment setup and thus produced a better coverage of the evaluations. The threshold value for quadtree partitioning is empirically set to 0.1.

![Table 1](image)

Referring to Table 1, it can be seen that the higher image pixel dimension influences PSNR and $C_{\text{ratio}}$ positively. Compression with larger images using the proposed method produces higher PSNR value but needs extra compression time. The PSNR value was decreasing with smaller compression time indicate the reduce quality of the reconstructed image, while $C_{\text{ratio}}$ is increasing with larger image size. Range blocks size influence the compressed image quality due to the less number of partitioned blocks. Therefore, the efficiency of similarity within domain and range block will reduce with minimal consumption of encoder execution time.

On average, it is observed that on different imaging modalities, $C_{\text{ratio}}$ for mammography is the highest as 410.19 with the PSNR 39.55 dB and $C_{\text{ratio}}$ of MRI is the lowest as 14.21 with a PSNR value of 25.76 dB. The outcomes reflect on the different size of image pixel dimensions. The results demonstrated that the proposed method can compress larger images better than small images. This is because large images allow the selection of multiple domains and ranges to be made. Therefore, the resulting fractal codebook becomes more accurate and allows it to be reconstructed properly at the decoder.

Overall, the proposed method can complete the compression task as fast as 3.42 s for the MRI images. The longest time was recorded by the mammography image of 57.02 s. This proves that if compression time can be reduced, by maintaining image quality, the FIC will be a more practical and affordable method in addressing the shortage of medical image storage size. A sample of compressed medical images for each modalities using the proposed method is shown in Figure 4. Visually, compressed images produced from larger pixel dimensions (Figure 4(c) and 4(d)) are much sharper compared to results generated using a smaller one, such as in Figure 4(a) and 4(b).
Figure 4. Sample of compression result of selected medical imaging modalities using the proposed method. (a) MRI, (b) CT, (c) CR and (d) mammography images, where (i) and (iii) are the original image (uncompressed) and compressed image at range (2,4) for MRI and CT, range (4,8) for CR and range (8,16) for mammography images. (ii) and (iv) are the closed-up view of each original and compressed images.

4. Conclusion
In this paper, an improved FIC based on peer adjacent mapping scheme and PCC domain classification is presented with providing a fast and better FIC compression performance. The performance of the proposed method is measured by using test image Lena as well as MRI, CT, CR and mammography images from established radiology image databases. Comparison with established
quadtreen-based FIC methods has been performed to assess the proposed method. Considering the experimental results, it is apparent that the proposed method able to compress various type of medical images in high compression ratio and demonstrates fast and good performance on compression time and PSNR scales.

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