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Efficient ROI-based compression of mammography images

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A R T I C L E I N F O

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MIAS database
PSNR
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A B S T R A C T

Medical imaging and telemedicine are progressively employed on a large scale these days. The utilization of lossless compression techniques for medical image storage and transmission may not provide significant benefits in terms of data reduction. On the other hand, the utilization of lossy compression techniques may lead to loss of essential data, which affects the diagnosis process. The critical data in the region of interest (ROI) of a medical image should be compressed with high-quality compression with no data lost or destroyed, regardless of the remaining parts of the medical image (non-ROI). Generally, mammography is used for investigating breast malignancies and localization of small tumors. Therefore, to increase the compression efficiency of mammogram images without losing any essential data, we present a hybrid technique based on lossless compression for the critical data in the ROI and lossy compression for the remaining parts of the medical image (non-ROI). In this work, edge-directed prediction lossless compression is adopted for the ROI, while fractal lossy compression is proposed for the non-ROI of mammogram images. Mammogram images from the mammographic image analysis society (MIAS) database are used to test the proposed hybrid technique. Encoding time, decoded image quality in terms of peak signal-to-noise ratio (PSNR), and compression ratio are the metrics used to assess the quality of compression. The obtained results prove that the proposed technique achieves a high compression ratio, while maintaining an acceptable quality of the reconstructed images compared with other recent mammogram image compression techniques.

1. Introduction

For females, breast cancer is one of the most common diseases. Mammography is the best accessible technology for the early detection of breast cancer at the moment. High-spatial-resolution X-ray mammogram images are used as a useful tool for achieving the goal of early diagnosis [1]. Mammogram images are complex, rough-textured images with a lot of diversity among the screening population, which makes detection and diagnosis more difficult. Furthermore, a significant amount of mammogram images is required for examination in any screening system.

1.1. Image compression importance in medical imaging

The volume of medical image data will continue to increase. It is a challenge to match the real-time transmission demands of large data sizes with the current capacity. The growing number of medical image archiving databases disseminated by healthcare providers has prompted research into not only expanding storage space and transmission capacity, but also investigating how to compress medical data efficiently. As a result, it is critical to use efficient image compression techniques to compress various medical images.

If we could achieve the research target of designing a system that safely allows effective data compression for primary viewing and storage, several benefits would be attained, including considerably lower storage costs, faster image viewing over networks, better access to an expert consultant, and speedier telemedicine. Lossless coding of digital mammogram images has been the focus of numerous studies. Li et al. [2] suggested grammar codes for converting mammogram images into context-free grammar, and compressing the context-free grammar using an arithmetic coding technique. Although high compression was achieved, it came at the cost of more sophisticated calculations and a longer computation time.

Neekabadi et al. [3] presented a lossless compression scheme of

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mammogram images through the chronological sifting of prediction errors and arithmetic coding for error coding. When comparing their scheme to JPEG-2000 and JPEG-LS on 50 mammogram images, it provided good compression ratios. Kumar et al. [4] offered an algorithm that divides the image into non-overlapping fixed blocks and codes the pixels within the blocks according to the degree of smoothness.

In [5], the lossless JPEG-2000 algorithm was compared to other lossless algorithms such as JPEG-LS, arithmetic coding, adaptive Huffman, and LZW with 12-bit and 15-bit dictionaries on digital mammogram images. The results showed that JPEG-2000 is preferred due to the several characteristics that aid in the transmission of reliable images, but it suffers from a slightly increased computational time. Recently, some researchers have used the artificial neural network power to archive digital mammogram images with an 8:1 ratio and a loss of 3 % [6].

1.2. ROI-based compression

Lossless compression techniques compress images without losses, but they have low compression ratios, while lossy compression techniques give high compression ratios, but sacrifice image quality, which is not desirable in the case of medical images. For medical images, selective compression is the ideal alternative to alleviate the limits of basic compression techniques. The main principle behind selective image compression is to divide the image regions into ROI and background (non-ROI) depending on their medical diagnostic information. Nasifoglu et al. [7] investigated different ROI sizes for adaptive compression of pelvis radiographs. The ROIs are chosen with different colors by the radiologist. The ROI marked with red color is defined as the most useful area for diagnosis, and it is encoded with lossless JPEG compression. Blue and green regions still contain diagnostic features compared to the rest of the image, but have less importance than the red region. They are encoded with the lossy JPEG algorithm with a high quality factor. The remaining region is considered as a non-ROI, and it is encoded with a low quality factor, as it does not have any diagnostic information.

For ROI coding of digital mammogram images, several approaches have been proposed. In [8,9], a lossy to lossless image coding system based on a combination of set partitioning in hierarchical trees (SPIHT) and integer wavelet transform was presented. Numerous images from the MIAS database have been used to evaluate this system, leading to an acceptable visual quality of the reconstructed images. In [10], a quantization vector with a competitive Hopfield neural network algorithm was used and applied on all ROIs in mammogram images with different compression ratios depending on their relevance to preserve vital information, while reducing storage or transmission size. This algorithm was tested using mammogram images from the MIAS database. The mammogram images are compressed with a high total compression ratio, while important medical diagnostic information is preserved.

In this paper, we focus on medical mammogram image compression. First, we divide the image regions into ROI and non-ROI, depending on their medical diagnostic information. Then, the ROI is compressed by edge-directed prediction lossless compression and the non-ROI is compressed by fractal lossy compression. Finally, the ROI and non-ROI are collected together to give the final compressed image and calculate the amount of compression. The main contributions of this paper are as follows:

- A simple and efficient ROI-based image compression framework containing segmentation and compression is presented.
- A fully-automatic ROI segmentation algorithm is utilized to get efficient and accurate results. Different previous algorithms for this task depend on user interaction.
- The proposed compression technique for mammogram images has been tested on 50 images from the MIAS database.
- The performance of the proposed technique is compared with those of recent mammogram image compression techniques to show the enhancement in compression ratio, while giving good-quality images.

The strategies for segmentation and compression are presented in Section 2. The experimental results are presented in Section 3. Finally, the concluding remarks are presented in Section 4.

2. ROI-based image compression framework

2.1. Overview of the proposed framework

For mammogram images, we propose an automated ROI-based image compression framework as shown in Fig. 1. In this framework, segmentation algorithms are used for separating the image into two uniform sections: ROI and non-ROI. Then, compression is used to handle the amount of data to be stored and the required bandwidth on the network. Two types of compression are used in this research: lossless compression for ROI and lossy compression for non-ROI.

2.2. Localization of the ROI

The most important part of the medical image is the ROI. It contains the most important information that should not be altered. The mammogram image segmentation is used to localize the ROI, and separate it from the surrounding areas. The pectoral muscle appears as a bright area (triangular region) at the top part of precisely imaged mediolateral oblique (MLO) mammograms. The presence of this bright area increases the complexity of automated diagnosis, as it would contradict image segmentation results, and the texture of the pectoral muscle could act as an ROI, which results in false positives (FP) in ROI segmentation. The removal of the pectoral muscle aids in localizing the ROI, automatically [11]. In digital mammogram images, as shown in Fig. 2, the ROI segmentation algorithm is divided into three stages:

- Pre-processing of the mammogram images.
- Delineation of the pectoral muscles using a biased normalized cut.
- Localization of the ROI using an optimal threshold.

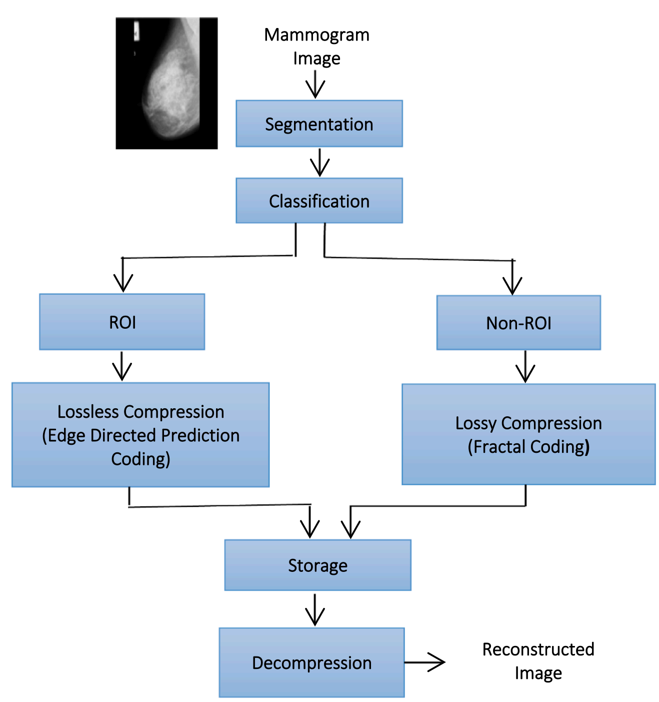

Fig. 1. ROI-based image compression framework.

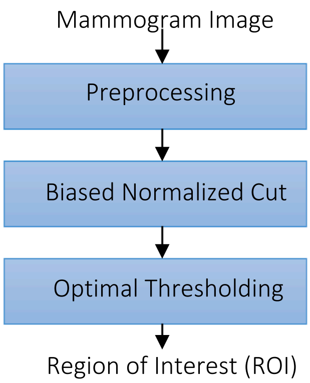

Fig. 2. Localization of the ROI.

2.2.1. *Pre-processing of the mammogram images*

Before the segmentation process begins, the mammogram images must be preprocessed by removing all background objects such as markings and stickers that are not part of the breast. A binary image is created by applying a very low threshold on the entire mammogram image. The breast has a huge surface area, which can be easily identified by computing the component areas. As a result, the breast is selected, and the mammogram image is adjusted to focus on the breast. These steps are presented in Fig. 3.

2.2.2. *Delineation of the pectoral muscles using biased normalized cut*

Firstly, the image is resized using nearest-neighbor interpolation after a preprocessing phase to reduce the processing time. Then, by defining 6 initial seed points at the Y-coordinate starting at the top of the breast region and collecting all pixels at a mean level around the intensity of the triangular regions of the mammogram images (pectoral muscles), we become able to separate the pectoral muscles from the mammogram images. The biased normalized cut is implemented based on the initial seed points [12].

During the mammogram image segmentation, the pectoral muscle component is identified. The edge of the defined region is rouged, while it is important to depict the edge smoothly. Therefore, Bezier curves are used as an effective way to visualize curves by extracting the control point for the Bezier curve representation from the edge of the segmented region. As shown in Fig. 4a, the pectoral muscle is outlined by the proposed algorithm, while the white dashed lines represent the ground truth outlined by the expert in Fig. 4b.

2.2.3. *Localization of the ROI using an optimal threshold*

Lesions appear as bright patches of varying sizes and gray-level intensities that depend on their surrounding tissues that appear dark gray. The segmented ROI is created using the appropriate threshold values derived using measurement of entropy after the pectoral muscle delineation. Figs. 5-7 show the segmented ROI results outlined by the proposed algorithm and the ground truth ROI specified by an expert.

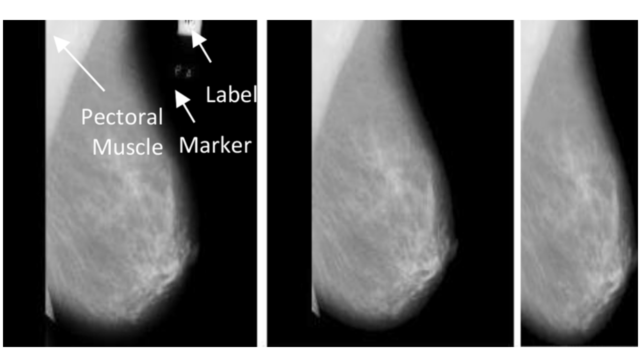

Fig. 3. Procedure for pre-processing of mammogram images.

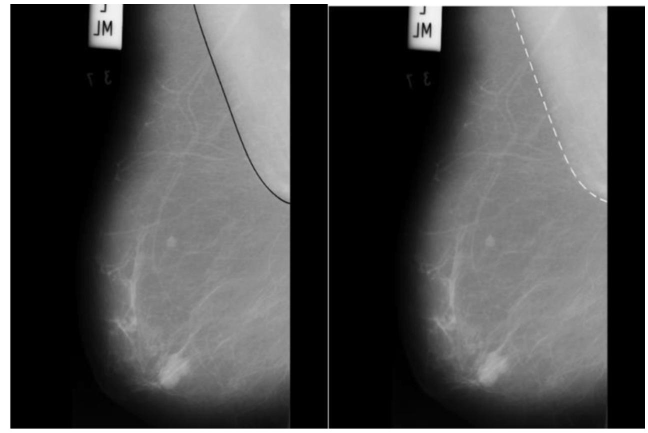

Fig. 4. The obtained results for (a) mdb005 (b) Ground truth by expert.

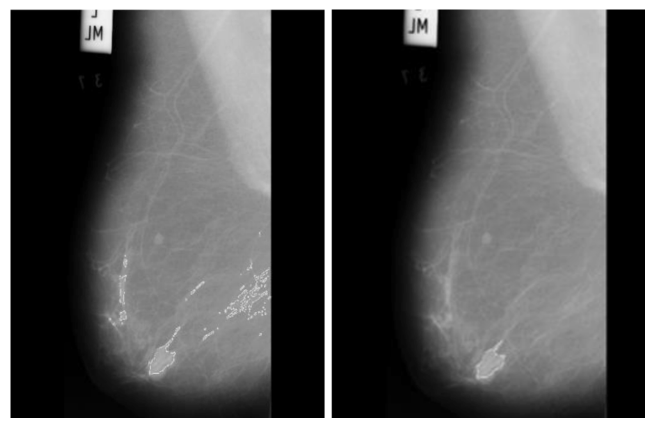

Fig. 5. Results obtained for localization of the ROI for (a) mdb005, (b) Ground truth by expert.

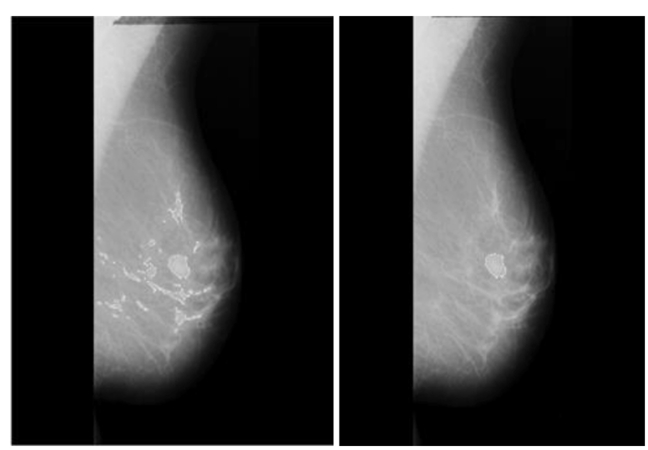

Fig. 6. Results obtained for localization of the ROI for (a) mdb010, (b) Ground truth by expert.

2.3. *Quality assessment*

The Jaccard similarity index (*JSI*) is used to quantitatively assess the proposed segmentation algorithm [13]. This index is calculated by comparing the obtained segmentation result *f* with the region outlined by an expert *g*. The Jaccard index *JSI* is defined as follows:

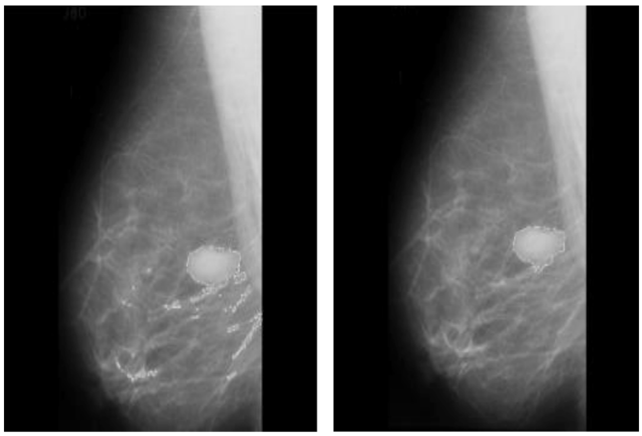

Fig. 7. Results obtained for localization of the ROI for (a) mdb025, (b) Ground truth by expert.

$$JSI = \frac{f \cap g}{f \cup g} = \frac{TP}{TP + FP + FN} \tag{1}$$

where *TP* represents true positive, *FP* represents false positive and *FN* represents false negative.

The pixel is allocated to *TP*, when a tumor is predicted and found in the ground truth. If a pixel is set as a tumor pixel but does not appear in the ground truth, it is allocated to *FP*. If a pixel is set as not a tumor but it is found in the ground truth, it is allocated to *FN*.

The *FN* results in the segmentation process should be minimized.

Table 1 summarizes the overall accuracy of ROI segmentation of mammogram images (Figs. 5-7).

2.4. ROI image compression

Lossless image compression ensures that the image can be restored properly without missing any data.

2.4.1. Edge-directed prediction lossless compression

In edge-directed prediction, the encoding and decoding of an image are done in raster scanning order. In the encoder, arithmetic and logic operations are performed in two passes. The first is for parameter computation, while the second is for data prediction and compression. The decoding process is a unique-pass procedure that decodes images based on the predictive model and encoder parameters.

The encoder presented in Fig. 8 employs context data for prediction. Hence, the context data for the current pixel is stored in the preceding two rows. Based on the pixel location and context, the predictor takes various decisions. Then, the predictor switches between binary and continuous operating modes based on the gradient sum. As most predictions are made near the edge pixels, adopting a gradient helps in producing better predictions in those cases. By accumulating errors in each context, the expected error in the context can be determined [14]. The gradient-based prediction *P* is improved by these accumulated errors through implementing the feedback system.

The predictor immediately switches to binary operating mode if the gradient quantity sums to zero. This binary coding approach improves coding capabilities in images with large patches of the same pixel intensity. The LS-based adaptive prediction techniques for compression were discussed by Xin Li [15]. Through the property of edge-directed LS–based adaptation, the orientation adaptation is obtained by analysis, and the optimal prediction is approximated.

Table 1
Quantitative comparison to evaluate the segmentation process.

Image name	mdb005	mdb010	mdb025
FP	0.5891	0.6832	0.2576
FN	0	0	0
JSI	0.4108	0.3167	0.7423

Assuming that the pixels are scanned in raster scanning order, the current pixel may be predicted using the previous causal data, namely context.

It is safe to assume that the image source has the n^{th} order Markovian property. The property of Markov sources is that the next state can be predicted based on the previous state. In the example of the causal neighbor for $n = 12$, we consider the N nearest causal neighbors in the prediction, as shown in Fig. 9. To predict the current pixel value, a linear combination of adjacent pixels is used.

$$X_e(n) = \sum_{k=1}^{N} a(k) \times X(n - d_k) \tag{2}$$

where X_e is the predicted pixel, X is the original image pixel, and $X(n - d_k)$ $(k = 1, 2 \ldots N)$ is the pixel causal neighbors.

$d_k = [i_k, j_k]$, where $i_k > 0$, $j_k > 0$ and $\sqrt{i_k^2 + j_k^2} \leqslant T$, where T is some threshold.

The least mean-square error (LMSE) optimization approach can be used to determine the linear combination coefficients $a(k)$. Locally, adapting the prediction coefficients to generate a smooth area around edges is possible with LS-based techniques. If the amplitude of the residue (i.e., the prediction error) exceeds a pre-determined threshold T, this amplitude can be used to distinguish and designate edge and non-edge pixels during the prediction process. If the LS optimization is turned on, the prediction will be updated; otherwise, the stored coefficients will be used to predict the next pixel.

2.5. Non-ROI image compression

2.5.1. Fractal image coding

Fractal geometry is a type of geometry that differs from Euclidean geometry. It helps in creating a shape that has an iterative nature. Fractal compression is based on the concept of self-similarity to codify an image, which means that very large compression of the information contained in the image is allowed based on self-similarity redundancy. This arises from the fact that part of the image is similar to the whole. Exploiting appropriately the self-similarities inside the image and expressing them through transformations are the foundations of fractal image compression [16–17].

2.5.2. Iterated function systems

The idea of iterated function system (IFS) is the mathematical concept on which fractal compression is based. In the proposed system, the image is divided into two types of blocks, and then we look for mapping between large blocks and small blocks. The large blocks are chosen as the code-words called the domain blocks, while the small bocks are mapped as range blocks. Then, we search for all domain blocks to find the domain block that has a close representation to the range block [18].

2.5.3. Basic scheme

Fractal compression constructs a unique approximation of the original image as:

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = w_i \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} l_{11} & l_{12} & 0 \\ l_{21} & l_{22} & 0 \\ 0 & 0 & s_i \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} d_x \\ d_y \\ o_i \end{bmatrix} \tag{3}$$

where z is the pixel intensity, (x, y) represent the spatial location of the range block, l_{11}, l_{12}, l_{21}, and l_{22} denote isometric symmetrical transformations, (d_x, d_y) are the contracted domain block spatial coordinates, s_i is a contrast scaling, $0 \leq s_i < 1$, and o_i is the brightness offset.

We search for the domain block in the domain pool, which has a close

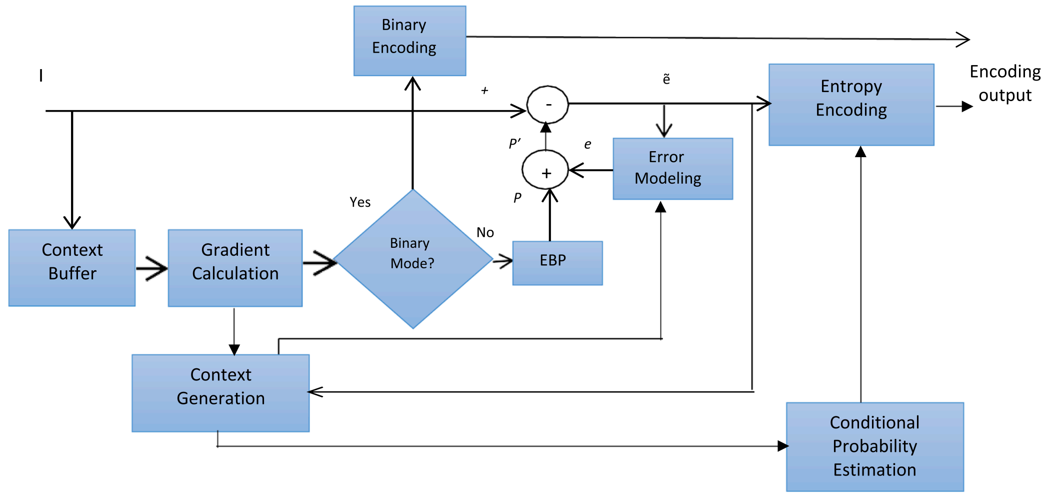

Fig. 8. Basic Block Diagram of the Proposed Edge Based Prediction scheme.

$X(n\text{-}11)$	$X(n\text{-}8)$	$X(n\text{-}6)$	$X(n\text{-}9)$	$X(n\text{-}12)$
$X(n\text{-}7)$	$X(n\text{-}3)$	$X(n\text{-}2)$	$X(n\text{-}4)$	$X(n\text{-}10)$
$X(n\text{-}5)$	$X(n\text{-}1)$	$X(n)$		

Fig. 9. Causal neighbor context window structure.

representation of the range block through checking which of the transformed domain blocks has a minimum distortion, when compared to each range block.

$$RMS(R_i, D_i) = \frac{1}{n}\sum_{i=1}^{n}(s.d_i + o - r_i)^2 \quad (4)$$

where s_i and o_i are computed by:

$$s_i = \frac{n\sum_{i=1}^{n} d_i r_i - \sum_{i=1}^{n} d_i \sum_{i=1}^{n} r_i}{n\sum_{i=1}^{n} d_i^2 - \left(\sum_{i=1}^{n} d_i\right)^2} \quad (5)$$

$$o_i = \frac{1}{n}\left(\sum_{i=1}^{n} r_i - c\sum_{i=1}^{n} d_i\right) \quad (6)$$

2.5.4. Encoding algorithm

The encoding algorithm can be summarized in the following steps:

1. The digital mammogram image needs to be partitioned into some non-overlapping square-size $[r \times r]$ boxes called range blocks R_i.
2. Also, the digital mammogram image needs to be partitioned into some square-size $[m \times m]$ boxes called domain blocks D_i with a size that is an integer multiple of that of the range block.
3. The domain blocks are reduced by averaging to keep the same size as that of the range blocks.
4. The range block is chosen as the block to be encoded, and the candidate domain block is chosen as the code-word. Then, we search for all domain blocks to find the domain block, which has the closest representation to the range block. The range block is then approximated as follows:

$$R_i = s.D_i + o.I \quad (7)$$

The values of (s, o) represent the affine scalar parameters calculated using the least squares method, and $0 \leq s < 1$.

5. The particular address of the domain block that provides the best match and the specific affine scalar parameters are saved into a compressed file. These mathematical transformations are the fractal code (IFS).

$$T(s, o, (i,j))_{best} \Rightarrow R_i \quad (8)$$

6. In the decoding stage, we need only to find any arbitrary initial image Ω with a size equal to that of the original image. By implementing an iterative algorithm (applying the IFS for a minimum of 10 times) for the sets of maps stored in the fractal codebook, we can get convergence into the final image.

3. Experimental results

The MIAS database is used in this research [19]. All used images are MLO and have a size of 1024 × 1024 pixels with 8 bits/pixel. The simulation software is MATLAB, and it is running on a PC with a 2.66 GHz processor.

3.1. Performance metrics

To evaluate the proposed ROI-based image compression technique, the following assessment criteria are considered:

1. Decoded image quality (*PSNR*):

The *PSNR* measures the quality of the decompressed image with 256 grayscale levels.

$$PSNR = 10\log 10\left(\left(255^2/MSE\right)\right) \quad (9)$$

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(I_{ij} - D_{ij}\right)^2 \quad (10)$$

where I_{ij} is the intensity of pixels in the input image and D_{ij} is the intensity of pixels in the decompressed image.

2. Compression Ratio (*CR*):

It determines the performance of the compression technique, and it is calculated as:

$$CR = \frac{\text{Uncompressed image file size}}{\text{Compressed image file size}} \tag{11}$$

3.2. Results and discussion

Proper medical image compression reduces the amount of data stored as well as the transmitted data during remote diagnosis. Millions of mammogram images are generated every year, worldwide. The coding of digitized mammogram images is worthwhile for the implementation of the best compression.

The primary intention of our research is to compress the mammogram images, efficiently. So, the mammogram image is initially preprocessed by removing all background objects such as markings and stickers that are not part of the breast. Otsu thresholding provides a good-quality binary image. Connected component labeling is used to label the different objects in the mammogram image. By computing component areas, the breast region is selected as the region having the largest area. Then, the pectoral muscle, which contradicts the ROI detection result, is separated using the normalized cut image segmentation. The biased normalized cut is implemented based on the initial seed points at the Y-coordinate, settled at the top of the breast region. This method is robust and accurate with large variations of positions of pectoral muscles. Then, the optimal threshold is used for determining the ROI and the non-ROI. The segmented ROI appears as bright patches of varying sizes and gray-level intensities that depend on their surrounding tissues. The main objective of the ROI compression is to localize the ground truth ROI i.e., localize the tumor, determine the lesion within the segmented ROI, and minimize *FN* results in the segmentation process (see Table 1). Afterwards, the ROI is compressed using a lossless edge-directed prediction encoding algorithm, while the rest of the image is lossy compressed using fractal encoding. In edge-directed prediction, the context window size, which approximates prediction coefficients, is chosen to be min(N,7). A window size larger than 7 does not further improve the prediction performance. For fractal encoding, the range block is chosen to be of size [8×8] and the domain block is chosen with a size that is an integer multiple of that of the range block. A mammogram image is a high-structural-similarity image. The optimal matching between the domain block and the range block is accelerated by reducing the capacity of the matching pool, thereby adjusting the speed of the fractal compression.

Fig. 10 shows the original image, ROI image, and overall reconstructed image, while Tables 2 and 3 summarize the performance of the proposed framework for mdb001, mdb002. mdb005, mdb010, mdb015, and mdb025 images. We see in Table 2 that there is no difference between input and output images after lossless compression. The reconstructed ROI image is quantitatively assessed giving a $PSNR = \text{Inf}$, which means that the decoded image retains all significant information of the original image. The encoded ROI and non-ROI are combined to give the compressed mammogram image, and the decoding algorithm reconstructs the image up to the desired quality level. Table 3 indicates the quantitative assessment with *PSNR* along with *CR* and encoding time for the overall reconstructed image. The results prove that the proposed hybrid compression framework is efficient, and it maintains an acceptable quality of the reconstructed images.

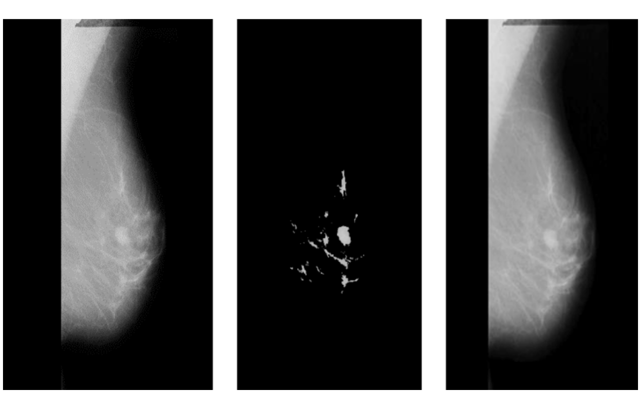

Fig. 10. Results obtained after compression and decompression (a) Original mdb010, (b) ROI image, (c) Reconstructed image.

Table 2
Assessment of the proposed compression framework for the reconstructed ROI of a mammogram images.

Name of image	PSNR (dB)	CR
ROI of mdb001	Inf	1.4
ROI of mdb002	Inf	1.3
ROI of mdb005	Inf	1.2
ROI of mdb010	Inf	1.4
ROI of mdb015	Inf	1.4
ROI of mdb025	Inf	1.3

Table 3
Assessment of the proposed compression framework for the overall reconstructed image.

Name of image	PSNR (dB)	CR	Encoding time(s)
mdb001	41.12	10.5	134
mdb002	36.83	11.44	120
mdb005	34.80	28.82	140
mdb010	43.85	36.75	129
mdb015	38.12	12.55	110
mdb025	35.03	22.01	157

Table 4 displays a performance comparison on 50 different images in terms of compression ratio for the algorithm presented in this paper, the base switching method [20], and the IWT-9/7-F [21]. As can be seen from Table 3, there is an enhancement in the compression ratio as compared to these methods.

4. Conclusion

For medical images, selective image compression is preferable. Therefore, to increase the compression efficiency without losing any essential medical data, we have proposed a hybrid compression framework based on intentionally separating regions into region of interest (ROI) and background (non-ROI) depending on their diagnostic significance. Then, a lossless compression technique is used for the diagnostically critical data in the ROI, while a lossy compression technique is used for the remaining parts of the medical images (non-ROI), which results in images with high compression ratios, and leads to maintaining acceptable quality levels of the reconstructed images. The obtained results prove that the proposed framework is reliable, and it achieves many benefits compared with other recent mammogram image compression techniques.

CRediT authorship contribution statement

Heba Abedellatif: Software, Validation, Writing, Review and Editing. **Taha E. Taha:** Visualization, and Investigation. **Ramadan El-Shanawany:** Data Collection, and Writing. **Osama F. Zahran:** Supervision, Experimentation and Writing. **Fathi E. Abd El-Samie:** Conceptualization, Methodology, and Software.

Table 4
Comparison on 50 mammograms in terms of average compression ratio.

Method	Base switching method [20]	IWT-9/7-F [21]	Proposed
Compression ratio	6.44	4.641	21.8

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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