Using Genetic Algorithm for Optimization of Mammograms Image Compression

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ABSTRACT:
In this study we created an optimized Region Of Interest (ROI) based JPEG2000 image compression algorithm for mammograms compression. The first step was to perform the standard JPEG2000 algorithm. The second step was to optimize this algorithm in different aspects which are, the type of wavelet transform, the number of decomposition levels of this transform and the quantization table for mammograms compression. Also we tried not to damage the diagnostic information in the images and keep the Peak Signal to Noise Ratio value, high. We achieved high compression ratios up to 165:1 with PSNR=47.96dB which was significantly higher than the previous results studied. At the next step we modified the optimized image compression algorithm in order to compress the mammograms with one square-shaped ROI in a way that we could compress the ROI losslessly. Therefore we could obtain a high total compression ratio and meanwhile preserve the significant medical diagnostic information. In previous studies on ROI-based 8bpp mammograms compression, the highest total CR for the ROI size of 5% and 15% of the entire image, with lossless ROI compression, were 32:1 and 12:1 respectively these values have been raised up to 49.9:1 and 21.33:1 in this study.

KEYWORDS: Mammograms Compression, JPEG2000, Optimization, Genetic Algorithm, Region of Interest.

1. INTRODUCTION

The technological advances in data storage and transmission have not kept up with the tremendous growth of digital data. This necessitates the development and use of novel compression techniques in all areas and especially in medical imaging, where the very large size of the images (~20-60 MB [1]) often creates serious challenges for their storage and transmission. In recent years, there has been a long-standing debate over which compression technique, lossy or lossless, is appropriate for the compression of mammograms, while lossy compression can achieve high CR[1]s, it has the risks of distorting the images, which may negatively affect radiological diagnosis. On the other hand, lossless compression can retain the important information in the image, but at the cost of very low and, thus, unacceptable CR). So it is vital to find an algorithm that can satisfy these two conditions (high CR and PSNR[2]) simultaneously.

DCT has found several applications in image compression and has become the base of some standard compression methods such as JPEG[3] so far and MPEG[4] for moving images. Conducted studies have shown that by optimizing the quantization table in JPEG, better results would be achieved [2]. Image compression by DCT based methods only offer good results in cases that all important clinical information in images are located in a narrow band frequency. It's clear that this is not true for most of the important details of medical images, because these details are usually not static and are not collected in a narrow frequency band. Also due to the blocky nature of DCT usually some blocking artifacts are found in reconstructed images. FF-DCT has been suggested as a solution for this problem. In image compression by FF-DCT the whole image is considered as an individual block and DCT is applied on the whole image. Therefore, with the cost of higher complexity in calculations, undesired blocking artifacts are avoided. Image compression by DCT- based methods offer better quality in reconstructed images at

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[1] Compression Ratio
[2] Peak Signal to Noise Ratio

[3] Joint Photographic Experts Group
[4] Moving Picture Experts Group

high CRs. This method is not suitable for MRI[1] and PET[2] images, because these images usually includes a circular-shape which the image intensity is zero out of it while FF-DCT stores images in a rectangular area, Thus in such images the coded picture includes an almost large area with zero intensity, which contains almost no information.

In lapped compression methods, some of the next blocks overlap with one another so some extra information related to the blocks edges is transformed. Therefore higher bit rates are necessary. In the filtering method the coding procedure at the transmitter side doesn't change but at the receiver side a low- pass filter is applied to borders pixels. Although this method does not increase bit rate, but it causes blurring in blocks borders. LOT has the advantages of lapped methods and also prevents bit rate increase.

Vector Quantization is the generalized version of the scalar quantization into higher space dimensions. This method does not maintain the information of the borders properly but it shows good results in compression of homogeneous areas in medical images with low bit rates and high quality, however it does not work so good in sharp areas with fast and sudden changes on edges. Since edges are so important in medical images, in order to compress these kinds of images, higher bit rates and code blocks with larger sizes should be used. This would make the computations more complicated.

In the Quadruplet Trees method, the redundancy and correlation between the image pixels are decreased by organizing or matching the transform coefficients. Through this method we can reach to CRS up to 10: 1, without losing any important clinical information. However, making the CRS higher in this method would lead to less precise diagnostics [3].

In image coding by wavelet transform, like the most other coding techniques we try to decrease the correlation between the pixels properly. If the basic function of the transform could compress almost all important information in a few coefficients, the others could be quantized or even considered as "0", without much distortion in the whole image. During the entropy coding, one of the common coding algorithms such as Arithmetic, Huffman, Run-Length or Bit- plane coding could be used. Besides of these general encoders, other encoders also can be used to encode wavelet coefficients, such as EZW, SPIHT and SPECK. The major difference between a wavelet transform based encoder system and other ones, is that in this system, unlike the others, there is no pre- processing on sub-images. The reason is that wavelet transforms are not only efficient according to calculation complexity, but

work locally on images. In the other word, basic functions have limited location amplitudes so it is not necessary to pre-divide the primary image into sub images. Since in a wavelet encoder the image is not divided into smaller pieces, undesired blocking effects (blocking artifacts) are avoided. While in other methods based on transforms, like DCT, blocking artifacts is one of the most important problems. In wavelet based methods even at high CRS these artifacts do not appear. The factors that affect the performance and complexity of the system and the reconstruction error are the type of the wavelet transform, the number of the decomposition levels and the wavelet coefficients quantizer.

In most cases artificial neural networks are used as an alternative to the other compression methods. For example neural networks could be used in order to determine Region of Interest (ROI), edge detection and similar applications before applying the other image encoding methods.

Fractal-based image compression is too complicated to be explained here. It is sometimes used to compress medical images. The major problem of this method is that it's based on blocking and therefore blocking artifacts problems will appear. So wavelet- based compression methods, in which one individual transform is applied on the entire image, are preferred [3].

One of the most efficient and important wavelet-based compression methods is the JPEG2000 algorithm. The steps and procedures of this algorithm are going to be explained in part 2 of this paper. The advantages of JPEG2000 rather than other methods have been proven before [4]-[5]. In [6], this algorithm has been compared to other lossless algorithms such as LZW, Adaptive Huffman, lossless JPEG, JPEG-LS and Arithmetic with zero degree and a first order probability model on mammograms. The results showed that although JPEG 2000 suffered from a slightly longer encoding and decoding delay than JPEG-LS, it is still preferred for mammogram images due to its wide variety of features that aid in reliable image transmission, provides an efficient mechanism for remote access to digital libraries and contribute to fast database access.

The JPEG2000 standard provides a set of features such as Region-of-Interest Coding, SNR scalability, spatial scalability, Error Resilience and the possibility of intellectual property rights protection. Interestingly enough all these features are incorporated within a unified algorithm [4].

Comparative results of JPEG, JPEG-LS and JPEG2000 from the functionality point of view are reported in Table 1. A plus (minus) sign indicates that the corresponding functionality is supported (not supported). The more the plus signs the greater the

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[1] Magnetic Resonance Image
[2] Positron Emission Tomography

support. The parentheses indicate that a separate mode is required. As it can be deduced from Table 1 the JPEG2000 standard offers the richest set of features in a very efficient way and within a unified algorithm [4].

Table 1. Comparative results of image compression algorithms [4].

Algorithm	JPEG	MPEG-4 VTC	JPEG-LS	JPEG2000
Lossless Compression	(+)	-	++++	+++
Lossy Compression	++	+++	+	+++
Embedded Bit stream	-	+++	+	+++
Region Of Interest	-	+	-	++
Arbitrary Shaped Object	-	++	-	-
Error Resilient	-	++	-	++
Scalable	(+)	++	-	++
Complexity	++(+)	+	++	+++
Random Access	+	-	-	++
Generic	+	++	+	+++

Even though the wavelet-based lossy coding shows promising results for mammographic images, the CBC[1] approach, introduced in [7]-[8] and discussed herein, provides a much desired compromise. CBC is a novel idea that combines lossless and lossy compression, together with segmentation. The lossless compression within the ROI is aimed to preserve the important image information, while lossy compression within the BG[2] helps to increase the overall compression ratio. One of the many applications of CBC is to compress medical images with a reasonably high CR, while preserving their diagnosis information.

The purpose of this study is to achieve optimized results in mammograms compression by JPEG2000. Although other successful studies have been done on these images compression by JPEG2000, this study has three exclusive features: 1-Image segmentation is done manually and by the user so it is possible to choose ROIs with desired sizes according to the type and size of the original image. 2-This algorithm is optimized in different aspects simultaneously by Genetic Algorithm. 3-An individual JPEG2000 algorithm is utilized in

order to compress ROI, losslessly and background, optimally. For example in [7]-[8] , CBC is done by independent lossless / lossy codes, while in the suggested method in this paper an individual compression JPEG2000 algorithm is used for ROI – based compression. Block diagram of this algorithm is shown in Fig.1.
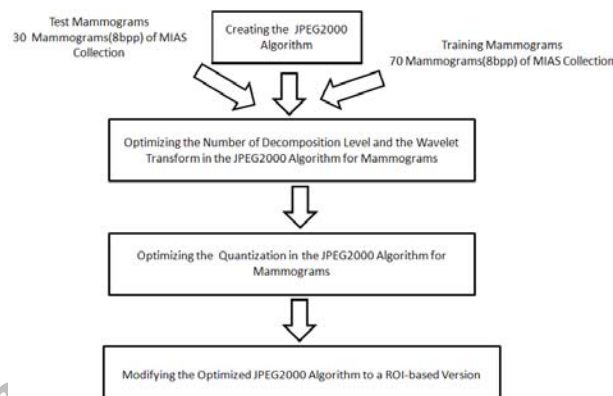

Fig. 1. The block diagram of the procedures of this study

This study is performed in three steps. At the first step, a version of JPEG 2000 is created. At the second step, this algorithm is optimized according to the number of decomposition levels of the wavelet transform and the quantization table for wavelet coefficients for mammograms and at the last step the final algorithm is modified and applied on mammograms in a way that ROIs could be compressed losslessly and Non-ROIs with loss, but optimally.

The organization of this paper is as follows: JPEG 2000 algorithm and the steps of its optimization are explained in sections 2 and 3, respectively. In section 4, the procedures of transforming this algorithm to a ROI-based version are going to be clarified. In section 5 the results are presented and in the last section, the conclusion is outlined.

2. JPEG2000 ALGORITHM

Encoding procedures are as follows: Tiling, Wavelet Transform, Quantization and Entropy Coding, which are going to be explained separately.

Tiling: First, the size of the tiles is defined, considering a square original image in a way all tiles have equal sizes and they cover the entire image without overlapping. In order to benefit from the advantages of image tiling and simultaneously escaping from its artifacts effects, the size of the tiles were defined as 512*512 and accordingly there were 4 tiles in each image based on the fact that the original image was 1024* 1024 pixels. Besides, in order not to lose the generality of the algorithm, we made it possible for the user to manually define any optional tile size according

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[1]Content-Based Compression
[2] Background

to the original image size such that the entire primary image is completely covered and tiles do not overlap. If each of the above conditions is not satisfied the user will be informed so he/she can define a correct size. Then the number of generated tiles and also the number of bits required to store the original image are calculated and recorded.

Wavelet Transform: The next step is to apply the wavelet transform on the tiles. Here, at first we created a lossy (irreversible) JPEG2000 algorithm. The default irreversible wavelet transform is "Daubechies 9- tap/ 7-tap" filter with 5 levels of decomposition [9]. By applying the wavelet transform, each tile is divided into sub-bands [9]. Quantization: Here, the wavelet coefficients are quantized, a procedure in which their precisions are going to be decreased. Each of the wavelet coefficients ($a_b(u,v)$), which belongs to b-sub-band, is quantized to $q_b(u,v)$ using (1) [4].

$$q_b(u, v) = sign(a_b(u,v))[\frac{|a_b(u, v)|}{\Delta_b}]$$
(1)

In (1), [   ] displays the nearest integer number less than the number inside it and Δ_b should be defined according to the dynamic range of sub-band b, R_b, by the exponent μ_b and mantissa ε_b as (2). The dynamic range R_b depends on the number of bits used to represent the original image tile component and on the choice of the wavelet transform [4]-[9].

$$\Delta_b = 2^{R_b - \varepsilon_b}\left(1 + \frac{\mu_b}{2^{11}}\right)$$
(2)

For the lossless compression, Δ_b should be defined as "1". This means $R_b = \varepsilon_b$ and $\mu b = \cdot$. The value of Δ_b is equal for each sub-band. Generation of Δ_b is done according to the function[1] specified in [9] (chapter 8). Clearly with 5 levels of decomposition we need 16 different values for Δ_b s related to 16 generated sub bands.

Entropy Coding: The last step is entropy coding which is Arithmetic Coding in the standard version of JPEG2000. Here we will not discuss about the details of this kind of coding. Finally the number of required bits to store the coded image is calculated.

The procedures of image decoding are the inverse of the encoding ones. In the other word, decoder acts inversely as of the encoder.

The generated code stream is going to be entropy decoded and then dequantized. At last the inverse discrete wavelet transform is applied and the data of the image is reconstructed. It is obvious that these

procedures, like the encoding ones, are done on each tile, independently.

At the first step of decoding, the inverse arithmetic coding is applied. The generated results are sent to the next step, which is de-quantization. Here the results from the previous step are going to be de-quantized by (3), which is a lossy procedure.

$$a_b(u, v) = q_b(u, v) \ * \ \Delta_b$$
(3)

In (3), q_b (u,v) s are the results of the arithmetic decoding and $a_b(u,v)$ s are the coefficients of b-sub band after de-quantization which need to be sent to the next step of reconstruction. Then the inverse discrete wavelet transform is applied and therefore the information of each tile would be reconstructed. After that, tiles are going to be located at their own positions till the entire image is reconstructed.

3. OPTIMIZING THE JPEG2000 ALGORITHM (TRAINING AND TEST)

Here we tried to optimize the developed algorithm for mammograms. The features considered for this optimization are as follows: the number of decomposition levels, the type of wavelet transform and the quantization table. In order to optimize these factors we divided the images into two separate groups randomly named "Training" and "Test" images. The steps of optimization performed are explained bellow.

During the training part, first we chose 70 (1024* 1024 -8bpp) mammograms belonging to MIAS[2] collection as the training population.

The first step of training is optimizing the type and the levels of decomposition in the wavelet transform for the training mammograms in a way that for each mammogram the compression results of each image is examined for the wavelets of "Daubechies, Coif lets, Symlets, Meyer and Biorthogonal" families and the number of decomposition levels vary from 3 to 9 and compared them with each other. It was observed that in 65 images, among the 70 selected mammograms, the best result of compression, according to CR and PSNR, were obtained at "Daubechies2" wavelet transform with 5 levels of decomposition. It is necessary to mention that in the other cases these conditions had the second degree according to the best CR and PSNR and also were very close to the best results.

The last step of optimization was to optimize the quantization table which was done based on Genetic Algorithm. This algorithm is one of the most important creative algorithms which are used to optimize different kinds of functions. In this algorithm, the information related to the last generation is extracted and used during the approach to the best answer. G.A has some advantages in comparison with the other

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[1] Step Size Function

[2] http://peipa.essex.ac.uk/info/mias.html

optimization algorithms. For example it searches the best optimal answer from different point of views, works on a collection of various variables simultaneously, starts with a collection of answers, not just one, so instead of finding one appropriate answer it recognizes an area in the space of variables, and by selecting parents based on their adequacies, it does a smart and efficient search that increases the chance to find the most optimal answer. In other words, it is not distorted by locally optimum answers. Of course the probabilistic- based nature of this algorithm does not mean that the searching approach is just random, but this kind of searching just works as an instrument that conducts the searching procedure properly. Here we are not going to discuss other detailed specifications and advantages of G.A in comparison to the other algorithms. G.A was recognized as the best choice here, according to the several variables which were considered in be optimized.

Based on (1), it is enough just to vary the values of Δ_b and then find the optimum ones. In order to find the optimum matrix, with the size of 1*16, we used G.A. Each of the variables of this algorithm was defined as the best one according to their own specific allowed range. The best package of values is offered bellow. The number of answers in each generation which are sent to the next one without changing[1] =2, the number of generations=100, the number of populations in each generation=10 and the mutation chance=0.7. Then given these parameters we defined the first population in 4 different groups as follows. One matrix exactly the same as the standard version of JPEG2000 with N=5[9], three random matrixes close to the standard one (with the variation amplitude of 5), in which like the standard one, the values of Δ_b s in each level of decomposition corresponding to the horizontal and vertical coefficients are the same and the one corresponding to the diagonal ones is different, three random matrixes, according to the allowed range of the standard matrix, with different values for vertical, horizontal and diagonal coefficients in each level and three completely random matrixes. Therefore we defined 10 matrixes of the first population. Then we calculated the fitness function value for each 10 matrixes and determined the parents. After then the children and considering the mutation chance, the next generation was generated and the procedure continued in the same way till the 100th generation where the fitness function converged. Here we found the best answer for each of the 70 training mammograms by this algorithm. The related results are given in the results section of this paper. In order to find the final

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[1] Num-Of-Elitism

answer we calculated the average matrix of the 70 generated matrixes and called it the final answer of the training procedure which is given in (4).

$$\begin{matrix} 540 & 570 & 626 & 496 & 475 & 528 & 579 & 610 \\ 455 & 362 & 380 & 392 & 339 & 356 & 370 & 354 \end{matrix} \quad (4)$$

During the test procedure the results achieved in the training part were tested on 30 test mammograms completely different from the training ones. First the test was done on the type and the number of decomposition levels in the wavelet transform as follows.

We examined whether or not N=5 and "Duabichies2" are the best choices for the test mammograms too, so we applied the JPEG 2000 algorithm with N=3 to N=9 and the wavelet transforms mentioned before on these 30 mammograms. It was shown that the best choices were N=5 and "Daubechies2" except for 2 mammograms in which these choices had the second best position and they provided CRs and PSNRs very close to the best results in each case.

In the next step, the results of the quantization optimization in the training part were examined on the test mammograms. First, the final-optimized matrix (4) was applied on these mammograms and the results were compared with the standard. It was found that the optimized matrix works more properly. You can find the detailed results in the conclusion section in this paper. Then we examined whether the final matrix is optimum for these mammograms or not, so we applied the previously introduced G.A on these images and found the best answer for each one and compared the results with the ones produced by the final–training-optimum matrix. The detailed results are shown in the conclusion section. As you can see, the final–training–optimum matrix has results which are very close to the ones produced by each mammogram's optimal quantization matrix, identified by G.A

Therefore the matrix in (4) was also recognized as the best choice for the test mammograms, which confirms the training results.

4. ROI-BASED OPTIMIZED ALGORITHM

The first step would be to select one ROI which can be done in several methods that can vary from extracting the entire mammogram from its dark background to fractal–based segmentation [1].In this paper, without losing the generality; we assumed the ROI is square-shaped. The user is requested to select a square with an optimum size as the ROI, at the beginning of the algorithm. After that, we separate the ROI from the non–ROI and considered it as an individual tile and compress it losslessly. Then we compressed non-ROI using the discussed optimized algorithm. The related block diagram is given in Fig.2.
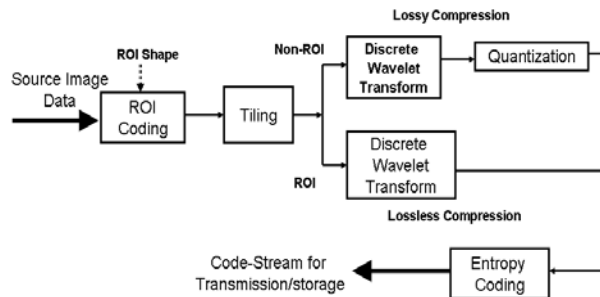
Fig. 2. Block diagram of the ROI-based compression algorithm

By this algorithm we can achieve the highest CR in BG (at the cost of losing some reasonable amount of information here) and in order to protect the vital information in the ROI, we compressed it losslessly by modifying the optimized algorithm to a lossless version through changing the wavelet transform to "tap/3-tap/5" filter [9] and defining N=3 and all the elements of the quantization matrix as "1", so the lost of data in ROI was minimum (at the cost of low CR s).

Two coding methods are defined in JPEG2000; "General Scaling" and "Maxshift". In both these methods a higher priority is assigned to the ROI coefficients rather than the BG, by being shifted up (or by shifting down the BG coefficients). But the difference between them is that in the general scaling method, the ROI coefficients are shifted by an optional value, while in Maxshift method they are shifted in a way that the least significant bit plane related to the ROI is higher than the most significant bit-plane related to the BG [10].

According to this fact, the General Scaling method makes it possible to have optional shift values but it also requires to send the ROI's shape information to the decoder and so it would highly decrease the coding efficiency(especially in the case of ROIs with random shapes). However Maxshift makes it possible to have ROIs with random shapes without generating any ROI–Mask [10]. It should also be considered that neither of these coding methods guaranties a completely lossless ROI compression so a specified final bit rate and a reversible wavelet transform are considered, in advance.

In this study we chose the Maxshift method. In the final generated bit stream the ROI's data are sent to the decoder before BG's and all of them along with the selected shift value were sent to the decoder, in which according to the amplitude of each coefficients, it is recognized that each coefficient belongs to either a ROI or a non-ROI. So the coefficients related to each region are going to be decoded through its own specific decoding procedure. By reconstructing each tile independently, the entire image will be reconstructed. At the end of the algorithm the values of CRs and

PSNRs related to ROI, non – ROI and the entire image are calculated independently.

5. COMPRESSION RESULTS

According to [1], JPEG can achieve CRs about 10:1 up to 20:1 for projection radiography images. According to [11], visually lossless wavelet based compression is accessible up to CR= 35:1. On the other hand, based on the results of [11]-[12], image compression using algorithms such as SPIHT [13] makes it possible to reach to CRs up to 80:1, without any noticeable difference between the original analogue and digital mammograms and as it is mentioned in [1]-[14] there is little difference between the reconstructed mammograms by JPEG2000 and the original ones, at CR=80, without damaging any diagnostic information. Based on the statistic studies in these references, at CR=15:1, there is not any detectable difference between the original and reconstructed mammograms, with the level of confidence equal to 99%.

In [15] a linear convolutional N.N-based research for an optimum wavelet transform with N=3 (without caring about the best choices for N and the quantization table) is done on head CT, 45 mammograms (12bpp), 120 microcalcifications (32*32 pixels) extracted from these mammograms and "Lena". The results showed that the "Daubechies" wavelets produce higher CRs and lower MSEs in many of the microcalcifications, mammograms and "Lena". Besides "Haar" wavelet works as the best wavelet in sharp edges and also areas with low noise rates such as microcalcifications and thus, has the best results in microcalcifications compression. It has been proven in [15] that by using a specific low-pass wavelet transform, with specific coefficients[1], the vital information of an image could be better protected, with higher quality and signal to noise ratio.

In [16] the impacts, the type of the wavelet transform on CRs values in artifacts compression and the reconstruction error in eight mammograms (512 * 512 -12bpp), all containing biopsy-proven malignant cluster of calcification (140*140) were observed. These images were compressed with CRs 5:1(with the running time equal to 50sec) to 195:1. The results showed that "Daubechies 4" hyperbolic wavelet transform was the best choice and could offer CRs up to 100:1 (with MSE =39) but at higher CRs the value of CR would increase suddenly and significantly. "Biorthogonal-1-3" and "Daubechies2" wavelets were the next best choices.

In [2], the best quantization table (a 8*8 matrix) for DCT coefficients in JPEG algorithm for X–Radiographs, US, MRI and CT compression was

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[1] 0.32252136,0.85258927,0.38458542,-0.1454869

studied. For each image one CR is specified and the best quantization table corresponding to this CR is found. In the beginning of this study, an optimized JPEG algorithm with CRs up to 42.151:1 and PSNR=41.51dB is also offered for mammograms, which is another reason that proves the superiority and better performance of JPEG 2000.

The comparative results of the quantization table optimization for training and test mammograms are given in table 2 and 3, respectively. The values of CRs, PSNRs and WSNRs are given as the average of each ten values of each ten images for summery.

Table 2. Comparative results of optimized and standard quantization.

Quantization method	Standard	Optimized
Training Images		
First ten mammogram	CR:55.12	CR:90.63
	PSNR:43.29	PSNR:44.30
Second ten mammograms	CR:51.29	CR:77.54
	PSNR:42.64	PSNR:43.89
Third ten mammogram	CR:54.03	CR:92.43
	PSNR:43.76	PSNR:43.98
Forth ten mammogram	CR:76.18	CR:127.50
	PSNR:45.60	PSNR:42.95
Fifth ten mammograms	CR:52.65	CR:82.28
	PSNR:43.72	PSNR:42.29
Sixth ten mammogram	CR:72.45	CR:127.36
	PSNR:45.37	PSNR:45.76
Seventh ten mammogram	CR:55.78	CR:90.29
	PSNR:43.43	PSNR:44.52

Table 3. Comparative results of the quantization optimization in Test mammograms

Test Images Quantization method	First ten mammograms	Second ten mammograms	Third ten mammograms
Standard	CR:64.44 PSNR:44.26	CR:56.39 PSNR:43.82	CR:53.11 PSNR:43.52
Optimized	CR=107.96 PSNR=44.36	CR=85.92 PSNR=44.13	CR=79.01 PSNR=43.88

We have compared the compression results of applying G.A on each image, individually and the final training matrix in test mammograms in table 4. The values of CRs, PSNRs and WSNRs are given as the average of each ten values of each ten images for summery.

The compression results of all 100 mammograms

(70 training and 30 test mammograms) compressed by optimized and standard JPEG2000 are shown in table5. The values of CRs, PSNRs and WSNRs are given as the average of each ten values of each ten images for summery.

In order to make the optimization results of this study more clear the best and worst images with the histograms of the error images are shown in Fig.3a and 3b.The best and the worst results were CR= 165.63, PSNR (dB) =47.96, WSNR (dB) =40.5 and CR=66.93, PSNR (dB) =42.85, WSNR (dB) =40.48, respectively.
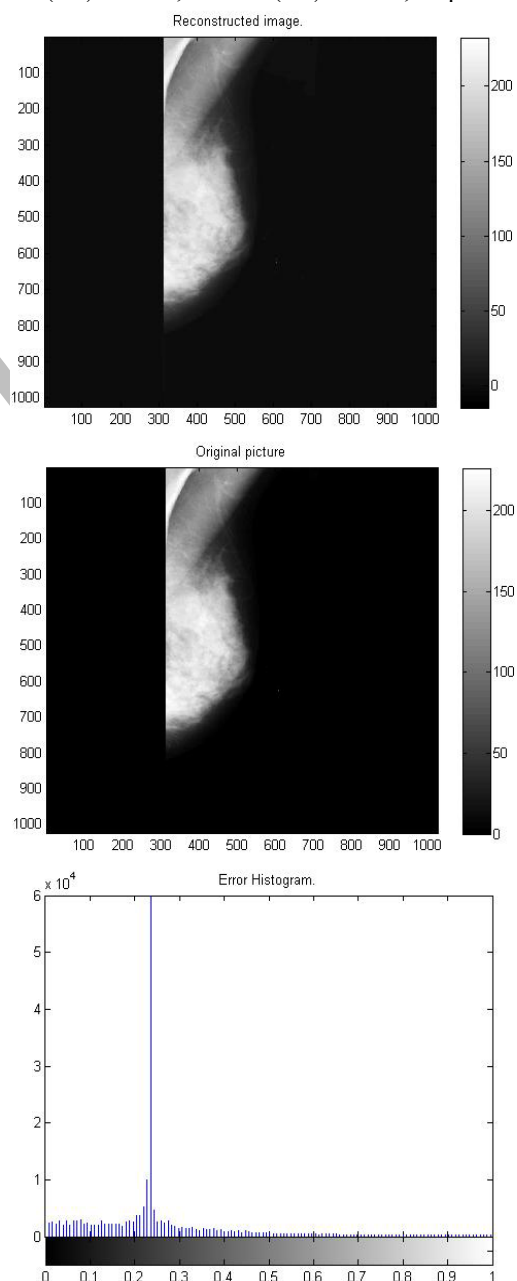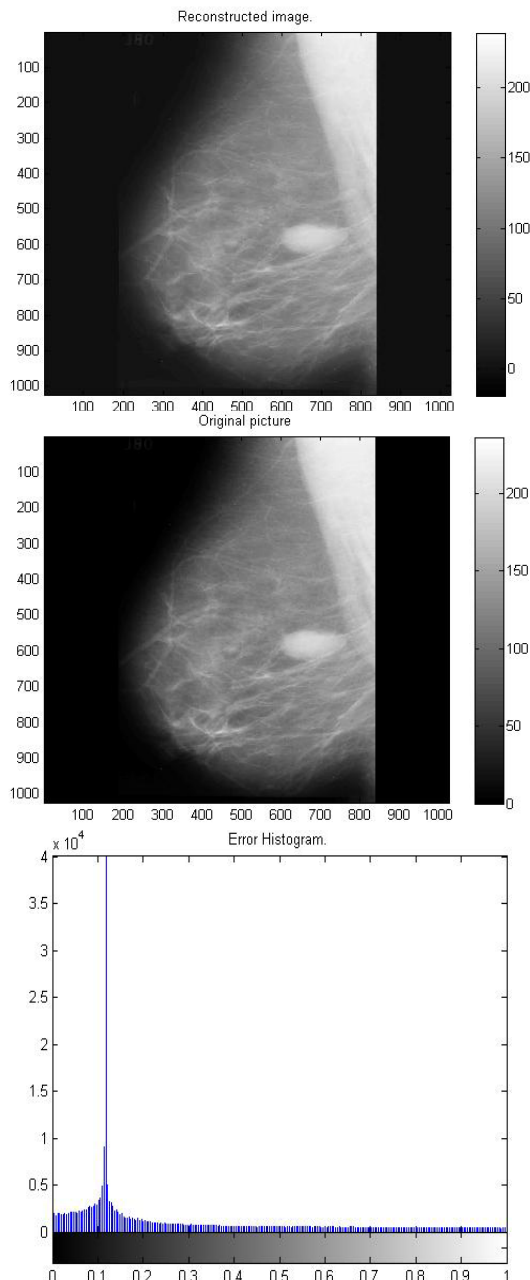

Fig. 3-a. The results of the best mammogram compression with the optimized algorithm.

Table 4. Comparative results of the optimized quantization table and the optimized table for each mammogram in Test mammograms

Test Images Quantization method	First ten mammograms	Second ten mammograms	Third ten mammograms
Applying G.A on each mammogram	CR=110.54 PSNR=44.06	CR=87.87 PSNR=44.34	CR=80.56 PSNR=43.12
Optimized	CR=107.96 PSNR=44.3	CR=85.92 PSNR=44.13	CR=79.01 PSNR=43.88

Fig. 3-b. The results of the worst mammogram compression with the optimized algorithm.

You can find the more detailed results of table 5 in the graphs of Fig.4, in which the compression results of 50 sample mammograms among with 100 selected mammograms of the MIAS collection using JPEG2000 algorithm before and after the optimization are compared obviously confirming the superiority of the optimized JPEG 2000 algorithm given in this study.

Table 5. Comparative results of 100 mammograms of MIAS collection by the optimized and standard JPEG2000 algorithm.

Compression algorithm Images	Primary CR PSNR WSNR	Optimized CR PSNR WSNR
First	44.13 43.86 46.14	90.63 44.30 41.66
Second	42.35 43.19 46.11	77.54 43.89 41.68
Third	43.78 44.42 46.20	92.43 43.98 41.65
Forth	48.98 46.27 45.870	127.50 42.95 41.23
Fifth	43.46 44.33 46.91	82.28 42.29 41.99
Sixth	56.47 45.82 45.06	127.36 45.76 40.54
Seventh	45.45 44.03 46.34	90.29 44.52 41.92
Eighth	49.29 44.93 46.17	107.96 44.3 41.71
Ninth	45.00 44.33 45.53	85.92 44.13 41.28
Tenth	43.96 43.77 45.65	79.01 43.88 41.47

Therefore the results of previous studies on mammograms compression have been highly improved in this article. In [10]-[11], which have used SPIHT-based algorithms, the highest achieved CR, without any considerable difference between the original and reconstructed image and considering any ROI, is 80:1, which is clearly low in comparison with this study (165:1). In [14] the highest CR obtained by JPEG 2000, while there is a little difference between the original and the reconstructed image and the diagnostic information are not damaged, is 80:1 which is again highly improved in this study. In [15] the optimum wavelet transforms for 12bpp mammograms are

introduced as "db" families, which is an acceptable result according to this study ("db2"). Besides, in this study more parameters have been considered in the optimization.
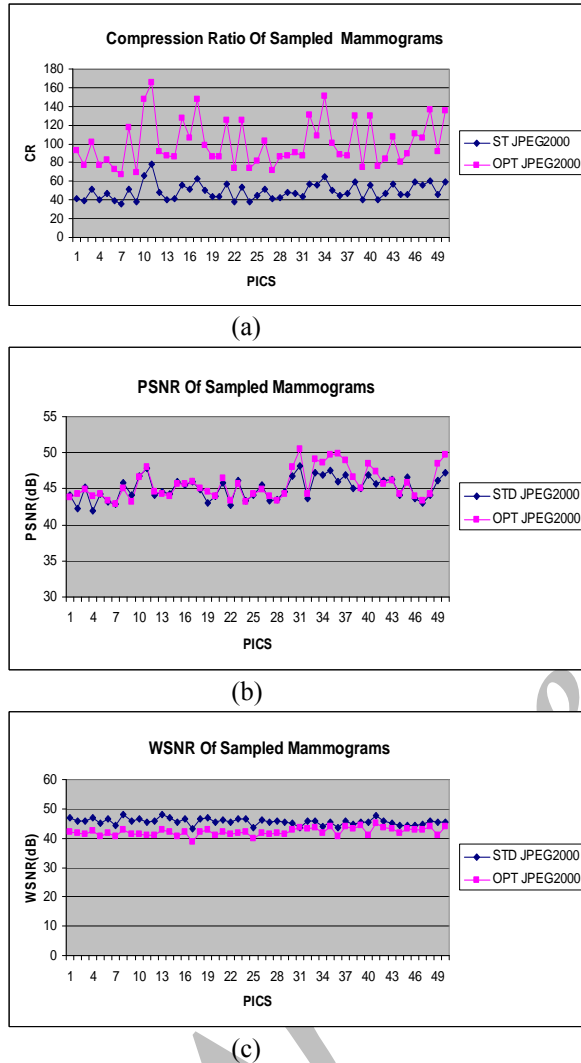

(a)

(b)

(c)

Fig. 4. Comparative results of the optimized and primary compression algorithm a) CR b) PSNR c) WSNR

In [16], the best wavelet transform to reduce the artifacts and increase the CR in mammograms compression with microcalcifications is identified as "db4", with CR=100:1 and PSNR (dB) =32.22, again not as high as this study's results (CR=165.63, PSNR (dB)=47.96). It is necessary to mention that "db2" in [15] is introduced as the third choice.

Reference [2] has not studied mammograms exclusively. As the result, it is said that at CR=15 there is no loss in diagnostic information but at CRs higher than 20, especially in ultrasonic images, blocking effects reduce the image's quality but suggests nothing

for these artifacts to be avoided.

ROI-based compression for mammograms is an idea to improve compression results, which according to [17] can averagely make increase CR by 5-10 times. In [7], this value is given as 5-6 times for mammograms used in data transferring.

In [1], the ROI is determined using fractal segmentation and then the mammograms were compressed by a modified JPEG2000 algorithm (ROI is compressed losslessly).

It is necessary to mention that the reason why we have used the results of [1] in this paper more than other similar studies is that it has the most similarity and also provides detailed results rather than the ones which have given just the summarized and general results.

In [1], the highest achieved CRs when ROI has the sizes equal to 5% and 15% of the entire mammogram are 32 and 12, while these values have reached up to 49.9 and 21.33, respectively for 8bpp mammograms as it is shown in Fig.5.
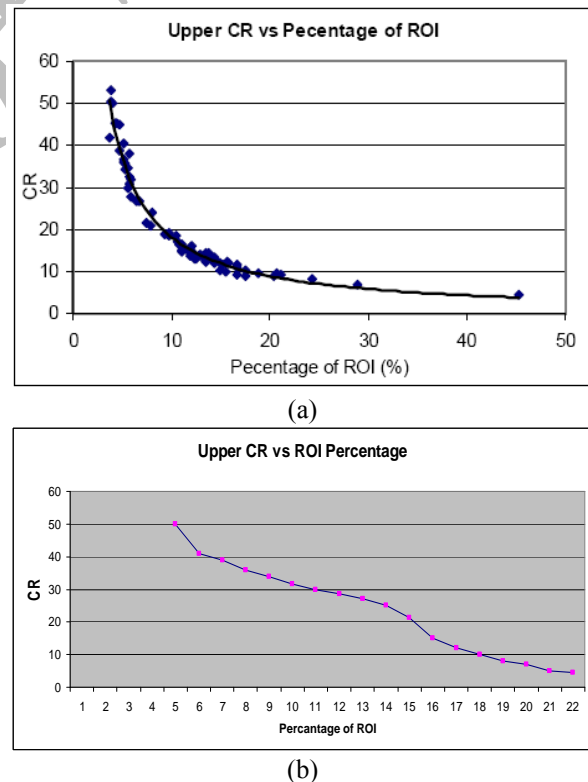

(a)

(b)

Fig. 5. Comparative compression results for the highest accessible CR according to the ROI size a) previous studies [1] b) this study

In Fig.6 the values of ROI MSE[1] in [1] for 8bpp mammograms are shown. By comparing these results

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[1] Mean Square Error

with Fig.6-b it is found that the values of MSE, obtained in this study are lower than the ones from the previous studies, which means reconstructed ROIs, here, have better qualities.

As it is shown in Fig.7 the values of CRs and total PSNRs in reconstructed mammograms by the optimized algorithm in this study, are simultaneously higher than [1] and also higher than the results of the same algorithm, before optimization.
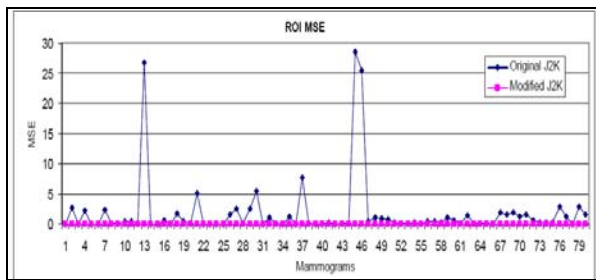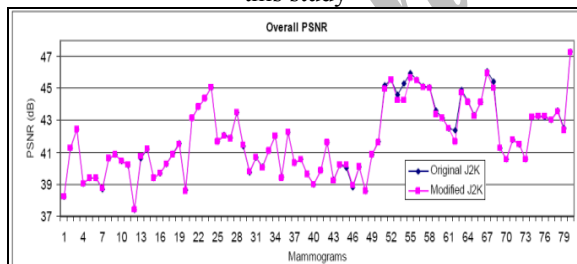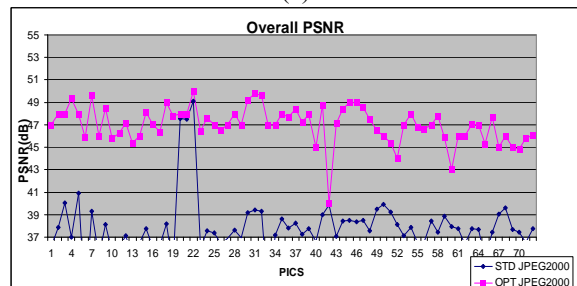

(a)
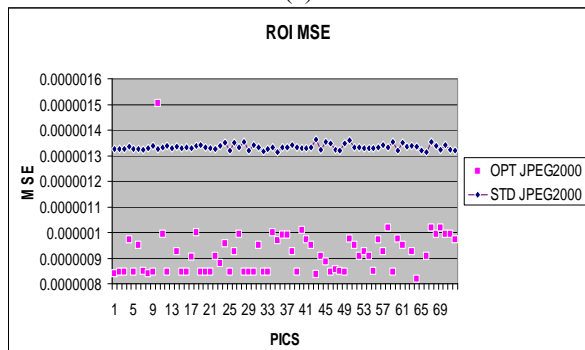
(b)

Fig. 6. Results of ROI MSE a) previous studies [1] b) this study

(a)

(b)

Fig. 7. Results of total PSNR a) previous studies [1] b) this study

In Fig.8, an estimation of results obtained of [1] for lossy compression of BG and lossless compression of ROI in mammograms is shown. As it's clear for 8bpp (1024*1024) mammograms, when the ROI size is equal to 15% of the entire image, the CR of BG could just be as high as 80:1 and so the total CR could reach up to 11.7 while, here, this value has reached to 21.33 and according to Fig.5-a, this information is seen for the other ROI sizes too (with lossless compression of ROI) In [1], some modifications have been applied on the standard JPEG2000 (sections 5-1 and 5-2 in [1]) in order to make it a ROI–based efficient algorithm. As you can see in this study these modifications are different and so much simpler and also have produced better results without increasing the complexity of the original algorithm.
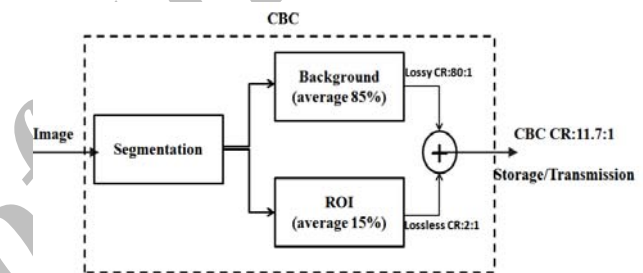

Fig. 8. An estimation of previous studies [1] for ROI-based compression.

Here, the results of the suggested algorithm simulation in MATLAB environment on the 100 selected mammograms are given. The obtained statistic results for a ROI size equal to 5% of the entire image is shown in Table.6. The values of CRs and PSNRs are calculated averagely, for each ten mammograms.

The images related to the ROI and the reconstructed mammogram with histograms of the non-ROI and the total error image in the best compression are shown in Fig.9. These results are as follows: CR=65.15, PSNR (dB) =46.82, for BG, CR=2.96, PSNR (dB) =106.90, for ROI and CR=49.90, PSNR (dB) =46.23, WSNR (dB) =48.87 for the total image.

The running time of the optimized JPEG2000 algorithm using a laptop computer[1] and MATLAB 7.0 was estimated to be 30 sec for each mammogram which is lower than the running time of [16] at CR= 50:1 (50sec) which leads to a faster algorithm with better results. The running time of the ROI–based optimized JPEG2000 without considering the time of selecting the ROI by the user, plus the required time of producing the compression results of the ROI, non–ROI and the total images, separately, was estimated as

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[1] Dell Inspiron 6400, CPU: Intel (R) Core(TM)2 , T7200@2.00GHz, 4MB cache.0.99 GB of RAM, Physical Address Extension

60 sec. It is necessary to mention that in order to find the best number of decomposition levels and the wavelet transform function the algorithm should be run for each one of the mentioned wavelet functions and the number of decomposition levels. The primary algorithm has the same running time as the optimized one at about 32sec. Besides, the required time to find the optimized quantization matrix for each mammogram, with the explained G.A, was estimated about 4 hours.

Table 6. Comparative results of 100 mammograms of MIAS collection by the optimized and standard ROI _based JPEG2000 algorithm.

Region Images	ROI	Total Image CR PSNR WSNR
First	CR:3.19 lossless	44.64 34.73 31.03
Second	CR:3.19 lossless	42.25 33.68 32.08
Third	CR:3.17 lossless	47.45 35.37 32.45
Forth	CR:3.21 lossless	46.62 36.55 34.67
Fifth	CR:3.44 lossless	38.95 34.57 31.45
Sixth	CR:3.43 lossless	45.26 36.34 34.68
Seventh	CR:3.50 lossless	42.29 34.25 31.35
Eighth	CR:3.11 lossless	46.32 34.58 33.23

6. CONCLUSION

In this study based on optimized ROI–based JPEG2000 algorithm for mammograms compression the following steps were done. 1-A JPEG2000 algorithm was created 2-This algorithm was optimized according to the type of wavelet transform, the number of decomposition levels of this transform and the quantization table for mammograms, which has been done for the first time. As the result of training and test procedures, the best chosen package was "Daubechies 2" wavelet transforms with 5 levels of decomposition and the quantization matrix of (4). For optimizing the quantization matrix we used G.A, which is one of the innovative aspects of this study.
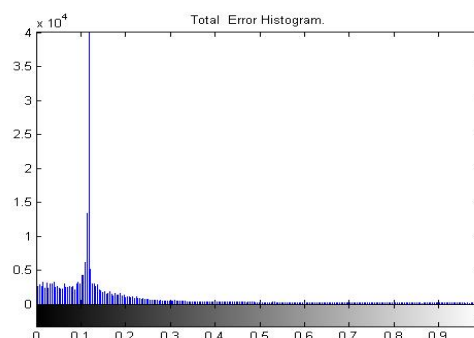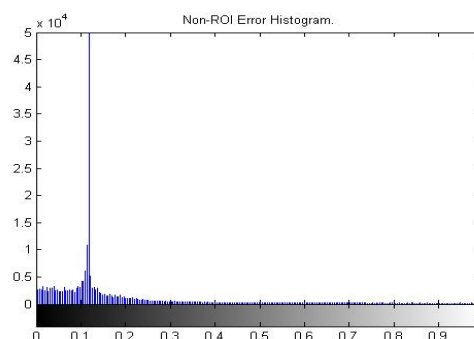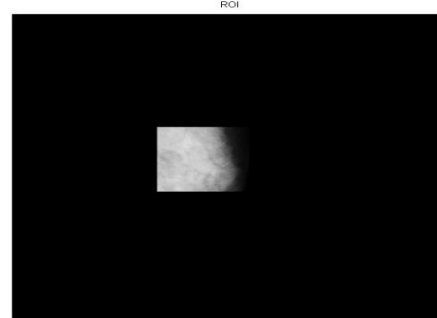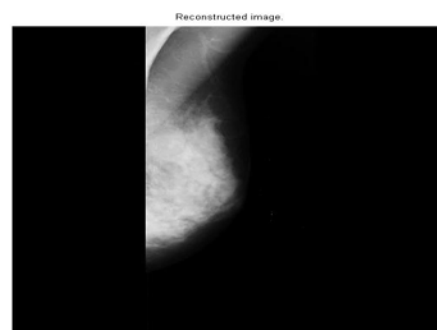

Fig. 9. The results of the best ROI-based mammogram compression with the optimized algorithm.

Here we achieved CRs up to 165.63 with PSNR=47.96dB and WSNR=40.85dB, which are rather higher than the results of previous studies (CR=80:1-100:1) [1]-[11]-[12]-[14]-[16]. Then, this optimized algorithm was modified to a ROI-based version in which ROI is compressed losslessly.

ROI was selected manually by the user and then coded by the Maxshift Method, which is the best choice for ROI coding in JPEG2000. Here because the ROI determination could be completely optional and the algorithm could also work for ROIs with optional sizes, it was preferable to select the ROI manually by user. The ROI was assumed to be square–shaped and the user is requested to choose a square as ROI in each mammogram. The BG was compressed using the optimized algorithm with the highest possible CR (at the cost of losing some reasonable amount of information here).

Then ROI was compressed by the modified lossless algorithm with the minimum loss of information (at the cost of low CRs).

In the proposed algorithm, we used one individual compression algorithm for ROI and non-ROI regions (unlike the studies of [15] and [17] which used two separate lossless and lossy encoders). In previous studies on ROI–based compression of mammograms, the highest achieved CR for a ROI size equal to 5% and 15% of the entire image with lossless ROI compression, were 32:1 and 12:1, respectively. This rate has been raised up to 49.9:1 and 21.33:1 in this study.

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