Content-Based Compression of Mammograms with Customized Fractal Encoding and a Modified JPEG2000

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Abstract. This paper describes a strategy for the content-based compression of mammograms. In this two-step strategy, the clinically important structures are first identified via a fractal-based segmentation method. Then, a modified version of JPEG2000 is applied in such a way that the extracted structures from the first step are compressed losslessly while the remaining regions are lossily compressed. Preliminary results clearly show that this strategy can achieve high compression ratios (5:1-30:1) without compromising the diagnostic quality of the mammograms.

1 Introduction

The technological advances in data storage and transmission have not been able to keep up with the tremendous growth of digital data. This necessitates the development and use of novel compression techniques in all areas but especially in medical imaging, where the very large size of the images (~20-60 MB) 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 compression ratios (CR), it risks 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 (~1.5-3:1).[1]

Recent trends tend to investigate the feasibility of compressing medical images with lossy coding at a threshold CR that is said to be *visually lossless*. Early studies indicate that JPEG can achieve a maximum CR between 10:1 and 20:1 for projection radiography.[1] Studies using wavelet-based algorithms indicate that visually-lossless compression is possible with CR as high as 35:1.[2] Studies from Ref. 3 even show that the wavelet-based SPIHT[4] compression algorithm can achieve a CR up to 80:1 with no significant difference between the original analog and the digitized mammograms. The latest Receiver Operating Characteristic (ROC) test with JPEG2000 also indicates that there is little difference between the original and the reconstructed images for CR as high as 80:1.[1] While in the same study, the statistical *t*-test shows no detectable difference between the original and the JPEG2000 decompressed images for CR up to 15:1 with 99% confidence level.

Even though the wavelet-based lossy coding shows promising results for mammographic images, the content-based compression (CBC) approach, introduced in Ref. 5, 6 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 regions-of-interest (ROI) is aimed to preserve the important image information, while lossy compression within the background (BG) 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. Our studies with mammograms indicate that the proposed CBC approach – which uses fractal-based segmentation together with a modified JPEG2000 – can achieve compression ratios up to 30:1, while fully preserving over 90% of the marked microcalcifications.

The organization of this paper is as follows. The concepts of content-based compression and fractal-based segmentation of mammograms are discussed in Sections 2 and 3, respectively. The standard JPEG2000 compression technique is briefly presented in Section 4 and our modifications to this standard are outlined in Section 5. Results of the application of the proposed CBC technique to mammograms with biopsy-proven microcalcifications and a comparison of these results with the original JPEG2000 ROI coding are included in Section 6. Finally, a summary of our findings and our current research efforts in this area are presented in Section 7.

2 Content-Based Compression

CBC consists of segmentation and compression processes. The segmentation process extracts the clinically significant structures (micro-calcifications, masses, ducts, etc.) from the images. We shall refer to these extracted regions as ROI. In the compression process, ROI are compressed losslessly, achieving high fidelity, while the BG regions (i.e., non-ROI) are compressed lossily, achieving high CR. Specifically, the ROI generation process employs a fractal-based segmentation technique and the compression process utilizes a modified version of JPEG2000. Based on our experiments, ROI comprise, on average, 15% of the mammograms with a good coverage of the clinically important regions. Figure 1 gives a preliminary estimate of CR in the proposed CBC strategy (~12:1), when assuming a 80:1 CR for the lossy compression of the background regions and a 2:1 CR for the lossless compression of the ROI.

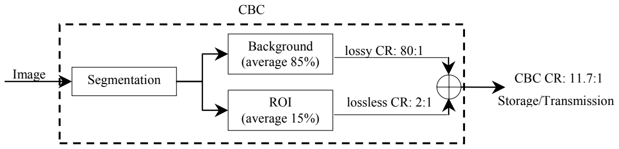


Figure 1. An estimate of CR for content-based compression.

Early works combining segmentation and compression for mammograms report a CR not higher than 9.8:1 (on average) with a near-lossless to lossless coding scheme for the extracted breast region.[7-9] Note that in these works, segmentation is limited to extracting the entire breast region from the background. The pilot studies from our previous works indicate that it is feasible to achieve an average CR of 18:1 (with ROI comprising around 10% of the mammogram), while preserving the image's diagnostic information.[5] In our previous work[5,6], CBC was achieved with independent lossless/lossy codecs, whereas the CBC approach discussed in this paper, uses a single, modified JPEG2000 compression engine with the reversible wavelet transform and the max-shift ROI coding method.

While others have used JPEG2000 for the compression of mammograms with considerable success, e.g., Ref. 1, our approach is unique in two ways: 1- Fractal-based segmentation of the breast region into ROI, and 2- Use of a modified JPEG2000 that assures lossless compression within those ROI.

3 Fractal-Based Segmentation

The extraction of significant structures from the mammograms is based on fractal encoding, which exploits the partitioned self-similarity property of the images.[10] This means that any sub-region of an image may be expressed in terms of another *similar* region via a mapping. This idea is very suitable for the extraction of significant structures in mammograms, because while the normal BG tissue is self-similar, it is structurally different from microcalcifications, masses, and ducts.[5]

The fractal-based segmentation process used in this work is a customized version of the standard fractal encoding technique given in Ref. 10. While the output of the standard fractal encoding process is the transformation parameters that best map partitions from the domain pool, **D**, to the partitions from the range pool, **R**, the output of our fractal-based segmentation is the *unmatched* regions. Our pilot studies.[11-13] indicate that the *unmatched* regions in mammograms along with their 8-connected neighbors largely contain the important diagnosis information, such as microcalcifications, masses, breast boundary and ducts. To reduce the complexity of the standard fractal encoding technique, we employ a *first-match* (rather than a *best-match*) scheme. That is, whenever a domain-range pair is found to satisfy the *match* conditions, the search for the best mapping parameters is terminated. This is shown to speed up the fractal encoding process by as much two times.[6] Another modification to the standard is the inclusion of the reduced-area 8-neighbors instead of the entire 8-neigbor partitions; see Figure 2. This is shown to essentially reduce the percentage of ROI without affecting the coverage of microcalcifications.[6] The following steps briefly outline this process.

1. The input mammogram is padded automatically and divided into 512x512, non-overlapping sub-images.
2. Each sub-image is partitioned into domain and range pools (using quadtree partitioning with a minimum level of $L_{\min}$), and the optimal parameters of an affine mapping are computed for each domain-range pair.
3. If the Root-Mean-Square error between the transformed pairs is less than a tolerance level, T, then the pairs are said to be *matched*.
4. Otherwise, the range partition is further partitioned and the previous two steps are repeated until a maximum partitioning depth of $L_{\max}$ has been reached.
5. Those sub-regions that do not satisfy the similarity condition (i.e., are *unmatched*) along with their reduced-sized, 8-neighbors are outputted to a binary mask file as ROI.

Figure 3 shows an example of ROI generation for a 10-bit mammogram with biopsy-proven microcalcifications with $L_{\min}$=4, $L_{\max}$=6 and T=6.7. Our previous studies, Ref. 5 and 6, show that this approach has a coverage rate (defined as the percentage of biopsy-proven microcalcifications contained within ROI) of over 90%.

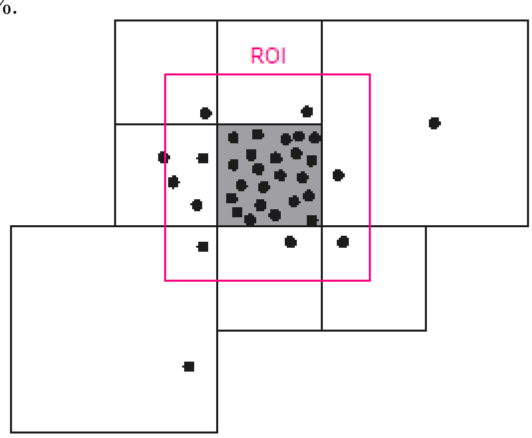


Figure 2. Visualization of microcalcification coverage for ROI comprising the *unmatched* partition (gray area) as well as its reduced-sized 8-neigbor partitions.

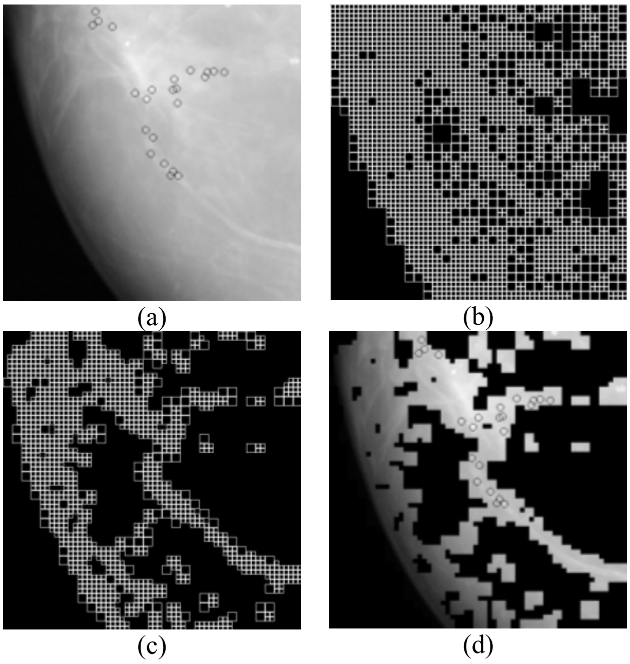


Figure 3. Example of fractal-based segmentation. (a) A part of mammogram with biopsy-proven microcalcifications (encircled), (b) quadtree partitioning of (a) as a result of customized fractal encoding, (c) sub-regions of (b) that satisfy the similarity conditions along with their reduced-area, 8-neighbors, (d) corresponding ROI, generated using the described procedure.

4 JPEG2000

Equally as important as the segmentation strategy is the choice of the compression engine. JPEG2000 is the recent ISO standard that emphasizes high image quality and low bit-rate. It provides many sophisticated functionalities, most relevant of which are: both lossy and lossless compressions, ROI coding, and rate allocation.[14] Figure 4 illustrates the core encoding engine of the JPEG2000 standard, which utilizes two-dimensional discrete wavelet transform (DWT), uniform scalar quantization with deadzone, and embedded block coding with optimized truncation (EBCOT)[15]. After DWT and scalar quantization (in case of lossy coding), the ROI coding is performed using the provided ROI shape information. Then, sub-band samples are partitioned into code blocks (typically 64x64 sub-band samples) and each code block is entropy coded independently with binary, bit-plane, arithmetic coder (EBCOT) to form a coded bit-stream. Each bit-stream contains a list of consecutive sub-bit-plane coding passes: significant propagation, magnitude refinement, and clean-up passes. Then, the bit-streams are truncated to achieve the desired CR using the post-compression rate-distortion optimization (PCRD_opt)[15] algorithm, and organized into layers and packets for transmission or storage.

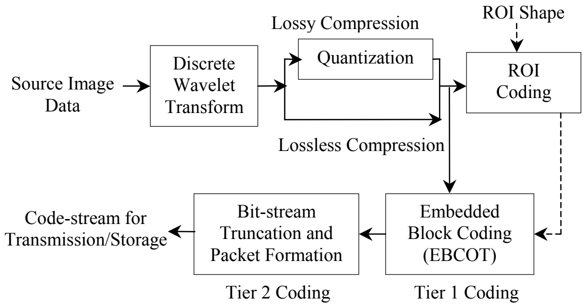


Figure 4. JPEG2000 core encoder.

4.1 *JPEG2000 ROI Coding*

Two types of ROI coding methods are defined in the JPEG2000 standard: 1- the general scaling-based method, and 2- the max-shift method. These methods give the ROI wavelet coefficients a higher coding priority than the BG coefficients by up-shifting the ROI (or down-shifting the BG) coefficients; see Figure 5. The general scaling-based method shifts the ROI coefficients up by a scaling value s, while the max-shift method shifts them up so that the least significant bit-plane of the shifted ROI is higher than the most significant bit-plane of BG.[16] The general scaling-based method allows different ROI to have different scaling values, but requires encoding and transmitting the ROI shape information to the decoder and, thus, greatly reduces coding efficiency (especially for an arbitrarily-shaped ROI). In comparison, the max-shift method allows an arbitrarily-shaped ROI and does not require the ROI mask at the decoder. [16]

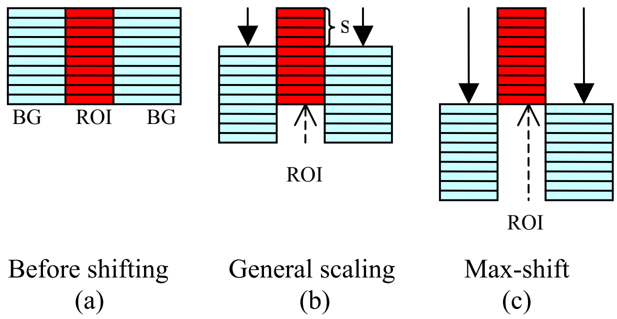


Figure 5. ROI coding: (a) before ROI coding, (b) general scaling-based method, (c) max-shift.

Although these characteristics make max-shift the method of choice for our application, it should be noted that neither of these techniques guarantee a losslessly compressed ROI when a final bit-rate with the reversible transform is specified. In addition to these techniques, two more advanced ROI coding methods were proposed recently.[17,18] While these possess the characteristics and the advantages of both the max-shift and the general-scaling based methods, they are not defined in the current standard and, more importantly, they too cannot guarantee a losslessly compressed ROI when a final bitrate is specified.

Images in Figure 6 demonstrate this shortcoming of the max-shift method when compressing an 8-bit mammogram with the reversible transform at CR 20:1 and using the Kakadu implementation of JPEG2000.[19] It can be seen from the decompressed image in Figure 6(c) (PSNR=10.69 dB) that even though a nearly lossless compression of the ROI was achieved (ROI MSE=2.34), the BG quality is unacceptable. If the max-shift method is not applied on the highest DWT level, a better compression result (PSNR=40.15dB) can be achieved with the same CR but a slightly poorer ROI quality (ROI MSE=2.39); see Figure 6(d).

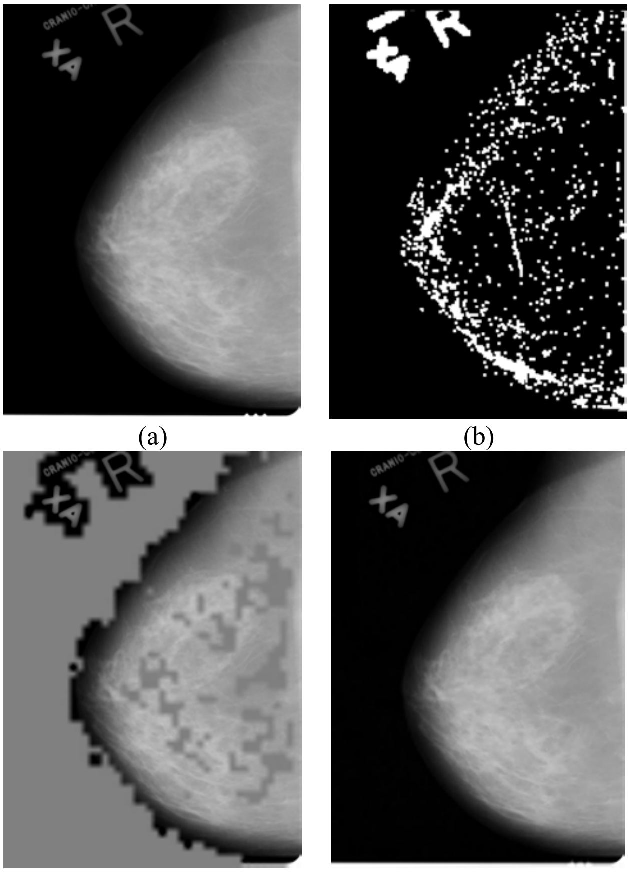


Figure 6. The inadequacy of the max-shift ROI coding method. (a) Original mammogram, (b) generated ROI mask, (c) reconstructed image when compressed with max-shift applied on the entire wavelet domain at CR 20:1, (d) reconstructed image when compressed with max-shift not applied on the highest DWT level at CR 20:1.

5 Modified ROI Coding in JPEG2000

Based on these findings, our aim was to modify the JPEG2000 encoder to ensure a lossless compression of ROI and a better BG quality for the same compression ratio. This was accomplished in two steps, which are outlined in the next two sections.

5.1 *First Modification*

To ensure a lossless compression of ROI with the reversible transform and a specified final bit-rate, the sub-bit-plane coding passes belonging to ROI coefficients, as generated by the entropy coder for each code-block, are prevented from truncation. This action is controlled by the EBCOT algorithm in the PCRD_opt stage of tier 2 coding.[14,15]

Figure 7 illustrates the difference between the bit-streams from the ROI and those from the BG code-blocks after max-shift. While the ROI code-blocks can have both ROI and BG coding passes, BG code-blocks contain only BG coding passes. Note that the total number of coding passes generated from a code-block before max-shift is

$$3K\_max\text{-}2, \qquad (1)$$

where K_max is the total number of bit-planes before max-shift, and there is no shifting on the BG code-block. Thus, after max-shift, the number of coding passes from a BG code-block remains unchanged, while the number of ROI coding passes from a ROI code-block is increased to

$$3(K\_\max' - K\_\max) - 2\,, \qquad (2)$$

where $K\_\max'$ is the total number of bit-planes after max-shift from a ROI code-block. Also, $K\_\max' = K\_\max + s$, where s is the number of bit-planes for BG coefficients that are down-shifted; see Figure 5. Our strategy is to prevent the ROI coding passes from truncation in tier 2 coding, while allowing the EBCOT algorithm to determine the truncation of the BG coding passes. This achieves a lossless compression of ROI and a lossy compression of the BG.

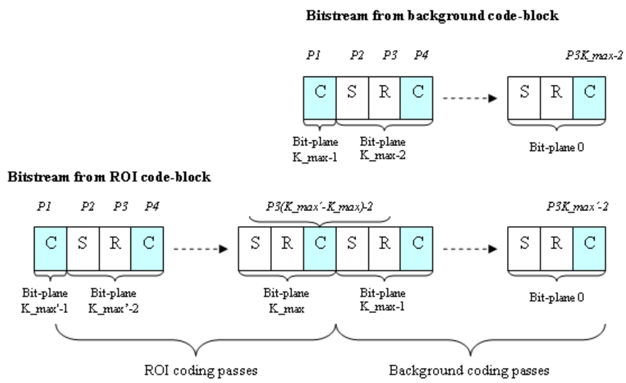


Figure 7. Difference in bit-streams between BG and ROI code-blocks with max-shift. “C”, “S”, and “R” refer to clean-up, significant propagation, and magnitude refinement passes, respectively.

5.2 *Second Modification*

In order to improve the visual quality of the BG and to provide a smoother transition between ROI and BG boundaries during progressive transmission, max-shift is not applied to the highest DWT level [the advantage of this is demonstrated in Figure 6(d)]. In addition, truncation of coding passes is not allowed in the lowest-resolution wavelet sub-band (LL sub-band) to ensure a minimum resolution for the BG regions. For the other three sub-bands from the highest DWT level (i.e., HL, LH and HH sub-bands), truncation for the coding passes of the BG code-blocks is determined by EBCOT, while truncation is not allowed for the bit-streams of the ROI code-blocks.

In the highest DWT level, the increase in the ROI bit-stream size (due to not truncating the coding passes from both the LL sub-band and the ROI bit-streams of the other three sub-bands) is partly compensated by not performing max-shift. This is because: 1- in the highest DWT level, the ROI code-blocks significantly outnumber the BG code-blocks, due to the fact that, theoretically, the code-block size remains unchanged for the entire wavelet domain; and 2- by not performing max-shift on the ROI code-blocks, which is the majority in the highest DWT level, we can increase coding efficiency.[16] In this way, the BG quality is improved and a losslessly compressed ROI is obtained without a significant increase in the overall ROI bit-stream size. Our experimental results show only a marginal increase of 1% - 2% in the overall ROI bit-stream size. Note that because ROI bit-streams are prevented from truncation, the resulting increase in the ROI bit-stream size will inevitably decrease the overall CR. However, the advantage of this modification is that it results in a significant increase in the BG quality and, thus, the final PSNR.

Figure 8 summarizes our modifications. Max-shift is applied at lower DWT levels, while truncation of the ROI coding passes is prevented. In the highest DWT level, instead of performing max-shift, truncation of the bit-streams from the ROI code-blocks is prevented, while truncation is allowed for the BG bit-streams. In the LL sub-band, however, both ROI and BG bit-streams are preserved. Figure 9(a) (PSNR=40.42dB) shows the reconstructed image with the suggested modifications at CR 20:1. Figure 9(b) is the arithmetic difference between this and the original image in Figure 6(a) after histogram equalization. It can be seen that the ROI is unaltered (ROI MSE=0.0) and a better BG quality with the same CR (20:1) is achieved.

5.3 *Coding Complexity and Compatibility*

To prevent the ROI coding passes from truncation in the PCRD-opt of tier 2 coding, one must first recognize the ROI and the BG code-blocks and compute the number of ROI coding passes that appear in the first portion of the

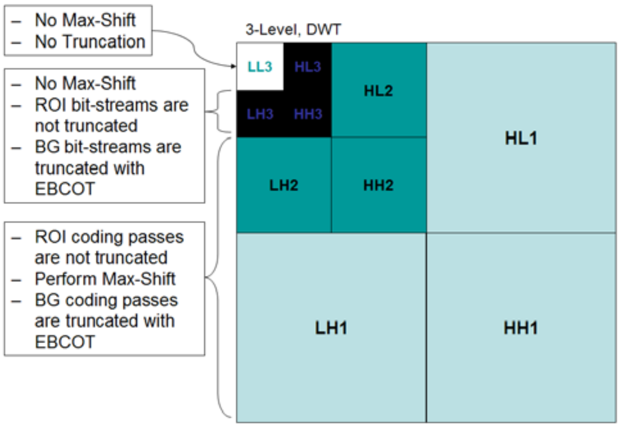
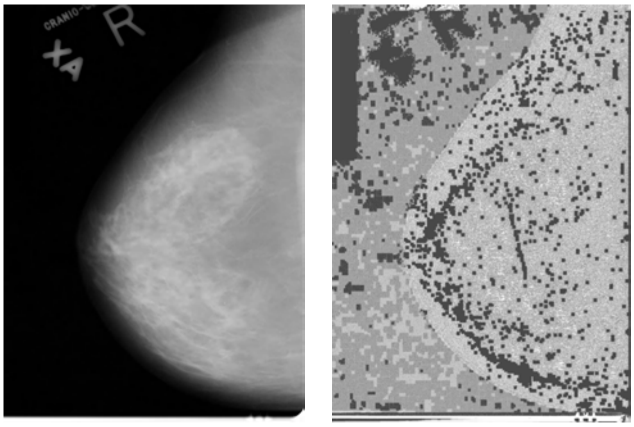


Figure 8 . Summary of modifications to ensure a losslessly compressed ROI and a high-quality BG.



(a) (b)

Figure 9. Modified JPEG2000 results. (a) Reconstructed image using the modified JPEG2000, when compressing Figure 6(a) with Figure 6(b) as ROI mask at CR 20:1, (b) arithmetic difference of images in (a) and Figure 6(a) with histogram equalization.

ROI bit-streams (see Figure 7). Then, the truncation can be prevented in one of two ways. First, one can simply set the length-distortion slope magnitude, λ, to zero.[14] Setting λ=0 for a certain coding pass essentially excludes it from the set of feasible truncation points and, thus, prevents the pass from truncation. The second method of preventing the ROI coding passes from truncation is to directly control it in the PCRT_opt algorithm. Because the encoder can distinguish between the ROI and the BG code-blocks, and it knows which portion of the bit-stream belongs to the ROI, it can directly prevent the ROI coding passes from truncation. In this way, the encoder has more control over the distribution of ROI coding passes in each quality layer. The results shown in this paper use the latter method to accomplish truncation prevention.

In summary, the advantages of our modifications are: 1- achieves a losslessly compressed ROI, while ensuring a good BG quality, and 2- the resulting code-stream conforms to the standard JPEG2000 format and no modifications are needed on the decoder side. Of course, because the ROI coding passes and the bit-streams from the LL sub-band are prevented from truncation, there exists an upper bound on the compression ratio, which the target CR may not exceed. This upper bound depends mostly on the percentage of ROI containing in the image and their distribution. Figure 10 predicts the nonlinearly decreasing trend of the upper bound of CR with increasing percentage of ROI.

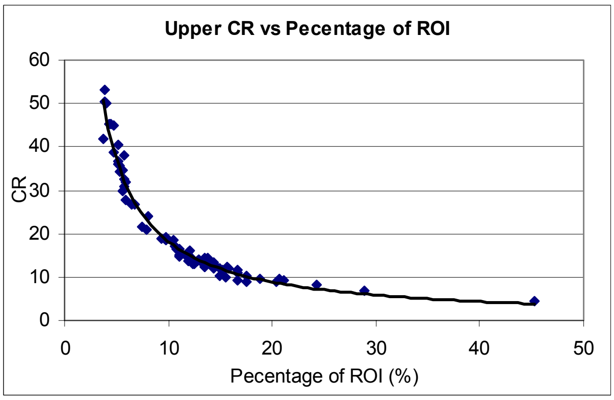


Figure 10. Predictive nonlinear relationship between the upper bound of CR and the percentage of ROI containing in the images.

6 Results

Eighty, 10-bit mammograms, obtained from the University of Chicago, are used to quantify the coverage rate of the fractal-based segmentation process, as well as the CR, MSE (Mean-Square-Error) and PSNR (Peak Signal-to-Noise Ratio) of the overall CBC strategy. Of these 80 mammograms, 22 are normal, and 58 have biopsy-proven microcalcifications or calcification clusters. Note that the abnormal mammograms are accompanied by files that contain the coordinates of the microcalcifications (as marked by expert radiologists), which provide the means for a quantitative assessment of microcalcification coverage rate.

The mathematical representations of MSE and PSNR are given as

$$MSE = \frac{1}{N_1 N_2} \sum_{n_1=0}^{N_1-1} \sum_{n_2=0}^{N_2-1} (x[n_1,n_2] - \hat{x}[n_1,n_2])^2 \tag{3}$$

$$PSNR = 10\log_{10} \frac{(2^B - 1)^2}{MSE} \text{ (dB)} \tag{4}$$

where x and $\hat{x}$ are the original and the decompressed images, respectively, and with sizes N_1 by N_2 and B bits per pixel. Clearly, with respect to the original image, large values of MSE indicate a poorer quality of the decompressed image, while higher PSNR values correspond to a better image quality.

6.1 Microcalcification Coverage

Figure 11 and Figure 12 predict the decrease of microcalcification coverage rate and the percentage of the original images comprising the ROI when increasing the tolerance level. Experimental results show that, on average, the microcalcification coverage rate for the proposed segmentation method is above 90% with ROI comprising approximately 10-20% of the entire image.

6.2 Modified Versus Original JPEG2000 ROI Coding

Graphs in Figure 13 demonstrate the advantages of the proposed modifications in comparison to the standard JPEG2000 encoder for the same CR. For the standard JPEG2000, the images are compressed with the reversible transform and max-shift is *not* applied on the highest DWT level. The ROI mask for each mammogram is generated by the fractal-based segmentation process, described in section 3, with T=6.7, L_{min}=4, and L_{max}=6. It is evident that the proposed modifications achieve *zero* ROI MSE, while the overall PSNR is comparable with the standard JPEG2000 encoder. On the other hand, the standard JPEG2000 encoder produces an unstable ROI MSE, which is quite undesirable for the application at hand.

7 Conclusions

It is evident from these results that a combination of a customized fractal-based segmentation and a modified JPEG2000 compression strategy gives rise to a powerful CBC approach that: 1- leaves the ROI, which contain clinically important information, completely unaltered, and 2- achieves respectable CR (up to 30:1) with high-quality reconstructed images (PSNR of above 40 dB and coverage rate of above 90%).

The advantage of our modifications to the JPEG2000 standard is that while preserving all of its merits (e.g., progressive transmission, rate allocation, error resilience, etc.), it produces a losslessly-compressed ROI (for high fidelity) and a lossily-compressed BG (for high CR) within a single compression engine. Also, the resulting code-stream is compatible with the standard JPEG2000 decoder.

Although a large-scale observer study is required to fully validate the proposed method, based on our to-date results, we believe that a strong foundation for the CBC of mammograms has been laid.

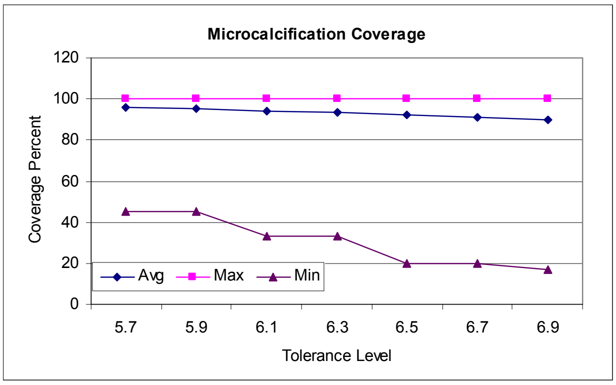


Figure 11. Microcalification coverage rate versus the tolerance level for the fractal-based segmentation.

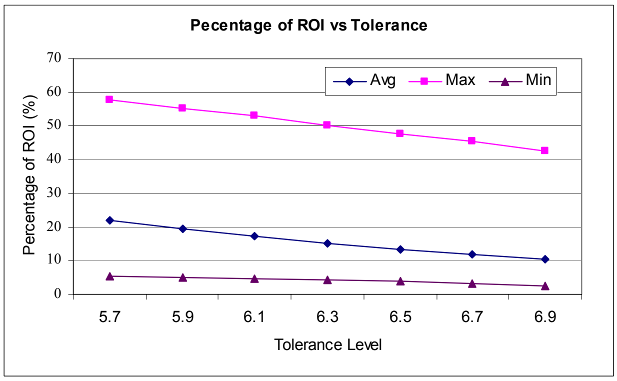


Figure 12.Percentage of original image comprising the ROI versus the tolerance level for the fractal-based segmentation.

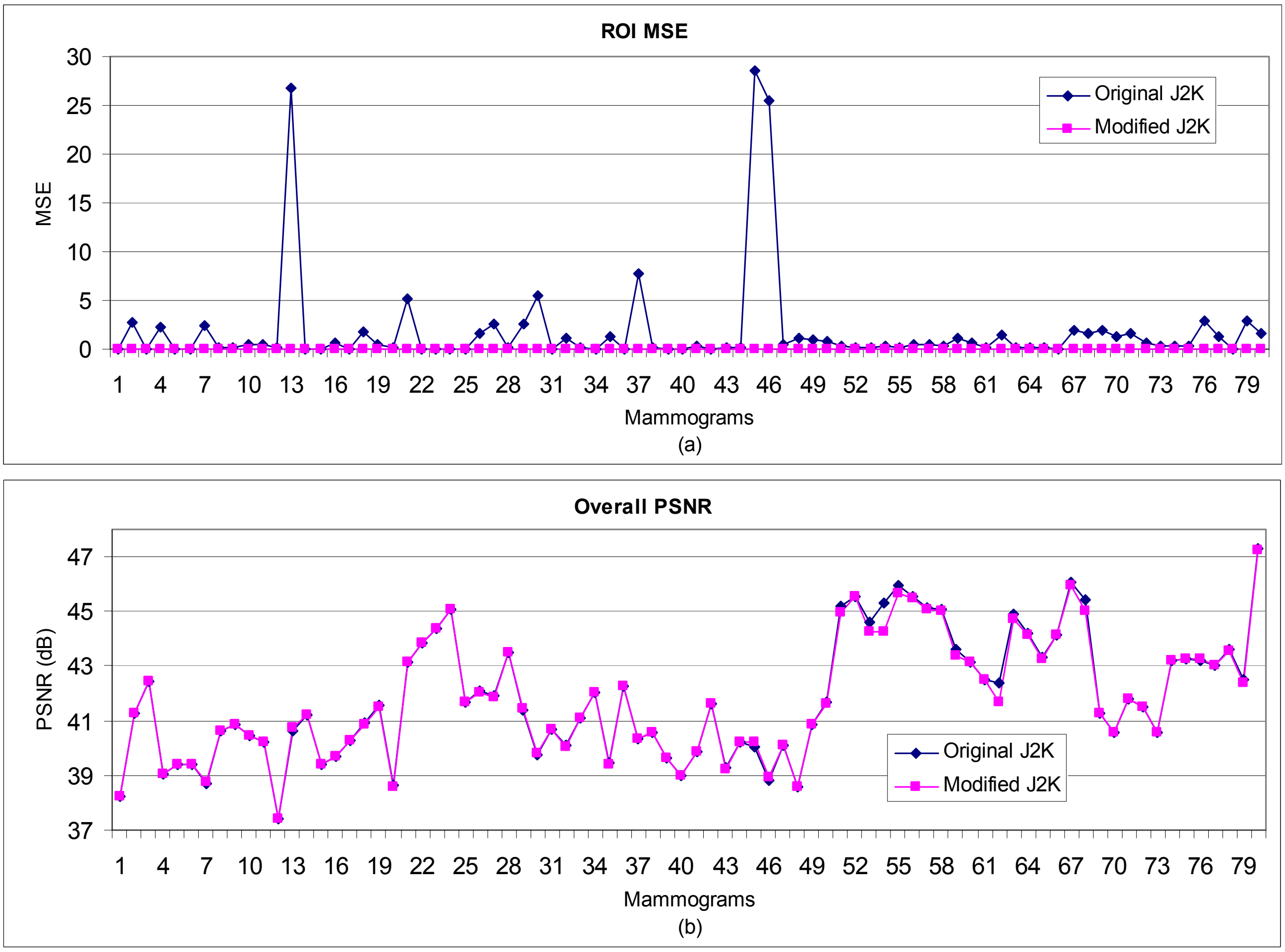


Figure 13. A comparison of the achieved (a) ROI MSE and (b) overall PSNR between the standard and the modified JPEG2000 coder.

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