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Performance Evaluation of ROI-based Image Compression Techniques

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Abstract- Medical diagnostic data produced by hospitals has increased exponentially. The coming era of digitized medical information and film-less imaging, has made it a challenge to deal with the storage and transmission requirement of enormous data. With this, selective medical image compression, a technique where explicitly defined regions of interest are compressed in a lossless way whereas image regions containing unimportant information are compressed in a lossy manner are in demand, day by day. Such techniques are of great interest in telemedicine which is a rapidly developing application of clinical medicine, where medical information is transferred through interactive audiovisual media. Archiving and retaining these data for at least more than two years is expensive, difficult and requires sophisticated data compression techniques. In the current research work, the focus has been solely on the performance evaluation on the ROI-based compression of medical images, but in a different prospective. The Mammogram images are used for the study. The image is divided into regions; ROI and the background. Then the arbitrary shape ROI breast region is compressed losslessly using losses image compression algorithms like SPIHT, JPEG2000 and Adaptive SPIHT. The background can be discarded or compressed as user's will. The work also introduces an ROI medical image compression technique that is able to assign priorities in case of multiple ROIs. Experimental results show that the proposed method offer potential advantages like extraction and integration of arbitrary shaped ROI, energy efficiency, ROI priority etc. in medical applications of digital mammography applications.

Keywords- Adaptive SPIHT, digital mammography, JPEG2000, SPIHT, Wavelets

I. INTRODUCTION

The American Cancer Society (ACS) [1] indicates that the probability of developing invasive breast cancer for USA's women younger than 39 is 1 in 210, and aged from 40 to 59 is 1 in 26. Mammography is the most effective way of detecting breast cancer before the onset of clinical symptoms [2]. The latest digital devices used in medical scenarios capture mammograms and angiograms images with a bit-depth resolution of 8-, 12- or 16-bits per pixel. In some cases, this high bit-depth resolution may produce files that grow to as much as 200 MB per mammography. Considering that current ACS guidelines for breast cancer screening recommend one annual mammography for women over 40 years of age, the increment in cost of both the transmission and storage capacity for mammographies is rising every year. A medical center that produces 20 mammograms per day, for instance, requires storage capabilities of more than 4 GB per day [3], and of more than 1.4 TB per year.

This brings a huge challenge to the current medical system. Compression is one of the indispensible techniques to solve this problem. For most medical images (digital mammograms), the diagnostically significant information is localized over relatively small regions of interest. In practice, the compression of medical images (digital mammograms) must be reliable because a minor loss may result in a serious consequence.

Due to clinical needs, lossless compression of medical images is often a sensible choice. Basically image compression techniques have been classified into two main categories namely: lossy and lossless methods. Lossy compression methods cannot achieve exact recovery of the original image, but achieves significant compression ratio. Lossless compression techniques, as their name implies, involve no loss of information. The original data can be recovered exactly from the compressed data. The fundamental goal of image compression is to reduce the bit-rate for transmission or storage while maintaining an acceptable fidelity or image quality.

One of the most successful applications of wavelet methods is transform-based image compression. The overlapping nature of the wavelet transform alleviates blocking artifacts, while the multiresolution character of the wavelet decomposition leads to superior energy compaction and perceptual quality of the decompressed image.

Previously, a new, fast and efficient image codec [4] based on set partitioning in hierarchical trees was proposed. This algorithm uses the principles of partial ordering by magnitude, set partitioning by significance of magnitude with respect to a sequence of octavely decreasing thresholds, ordered bit plane transmission, and self-similarity across scale in an image wavelet transmission. In 1996, the JPEG committee began to investigate possibilities for a new still image compression standard to serve current and future applications. This initiative was named JPEG2000 [5]. Selective medical image compression [6] is achieved by extracting region of diagnostic importance in course of achieving energy efficiency, then coding ROI and the background with a combination of JPEG2000 and SPIH. More recently, JPEG2000 ROI coding through component priority for digital mammography [7], has introduced a ROI coding method that is able to prioritize multiple ROIs at different priorities guaranteeing lossy-to-lossless coding.

It has been observed that when we compress a variety of images of different types using a fixed wavelet filter, PSNR, correlation, time to encode and time to decode vary widely from image to image, with multiple regions of interest. These variations can be attributed to the nature and inherent characteristics of the mammograms.

The rest of the paper is organized as follows: In section 2, the preliminaries for the wavelet based image compression are presented. Section 3, entails the different wavelet encoding methods. In section 4, error metrics are discussed for the purpose of evaluation. In section 5, the proposed methodology is presented. Section 6 presents the experimental results. The paper concludes with section 7.

II. Preliminaries

Wavelet-based image processing methods in general have gained much attention in the biomedical image community. Most medical images have smooth color variations, with the fine details being represented as sharp edges in between smooth variations. The low frequency components (smooth variations) constitute the base of an image, and the high frequency components (the edges which give the detail) add upon them to refine the image, thereby giving a detailed image. Separating the smooth variations and details of the image can be done in many ways. One such way is the decomposition of the image using a Discrete Wavelet Transform (DWT) [4], [8]. Wavelets are being used in a number of different applications.

III. Wavelet based coding methods

A. Set Partitioning in Hierarchical Trees

The SPIHT [4], [9] is a highly refined version of the EZW algorithm and is a powerful image compression algorithm that produces an embedded bit stream from which the best reconstructed images in the *mean square error* sense can be extracted at various bit rates. Some of the best results-highest PSNR values for given compression ratios-for a wide variety of images have been obtained with SPIHT. Hence, it has become the benchmark state-of-the-art algorithm for image compression [10]. Naturally most of the image's energy is concentrated in the low frequency components. A tree structure called, spatial orientation tree, naturally defines the spatial relationship on the hierarchical pyramid.

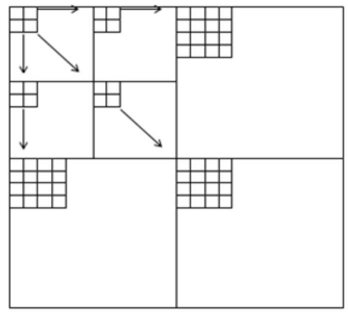

Fig.1. Parent-offspring dependencies in spatial orientation tree

The Fig1 shows how the spatial orientation tree is defined in a pyramid constructed with recursive four-band splitting. Each node of the tree corresponds to a pixel and is identified by the pixel coordinate. Its direct descendants (offsprings) correspond to the pixels of the same spatial orientation in the next finer level of the pyramid. The tree is defines in such a way that each node has either no offspring or four off springs, which always form a group of 2x2 adjacent pixels. The pixels in the highest level of the pyramid are the tree roots and are also grouped in 2x2 adjacent pixels.
With this algorithm, the rate can be precisely controlled because the transmitted information is formed of single bits. The encoder can estimate the progressive distortion reduction and stop at a desired distortion value.

B. JPEG2000

JPEG2000 is superior to the standard JPEG in having higher compression ratio, embedded bit stream, multiple resolution representations, error resilience, and region of interest coding [4]. JPEG2000 [11], [12] combines embedded block coding with optimized truncation (EBCOT) technique with lifting integer wavelet transform to offer plenty of advanced features. It is able to provide a high performance lossless medical image compression that is superior to JPEG standard at low bit rate. Two ROI coding methods, scaling-based and Maxshift are supported in part 1 of JPEG2000 [12]. The scaling-based has the advantage of allowing partial coding of the background region to the coding of the entire ROI, but it must transmit the side information of ROI

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at an additional coding cost. In the Maxshift method, the ROI bit stream is arranged in front of the background bit stream, so that the bit stream does not need to transmit additional side information to locate the ROI. The following figure focuses on the JPEG encoding procedure.

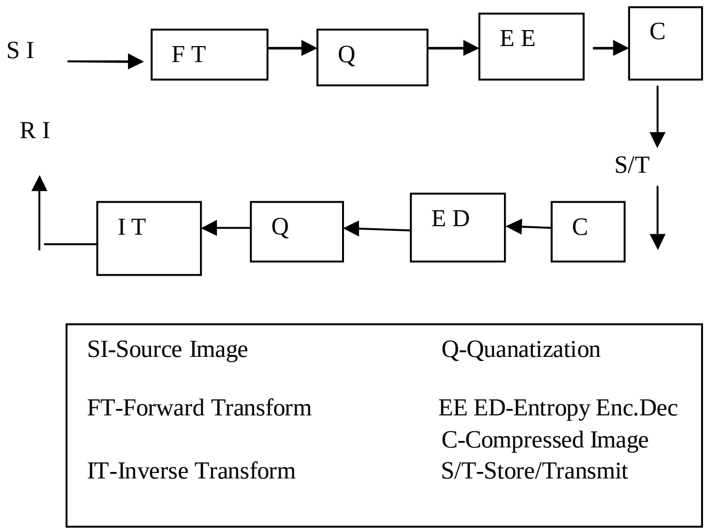

Fig.2. JPEG Encoding

The encoding procedure [13] is as follows:

- The source medical image is decomposed into components.
- The image and its components are decomposed into rectangular tiles. The tile-component is the basic unit of the original or reconstructed image.
- The wavelet transform is applied on each tile. The tile is decomposed in different resolution levels.
- These decomposition levels are made up of sub bands of coefficients that describe the frequency characteristics of local areas (rather than across the entire tile-component) of the tile component.
- Markers are added in the bit stream to allow error resilience.
- The code stream has a main header at the beginning that describes the original image and the various decomposition and coding styles that are used to locate, extract, decode and reconstruct the image with the desired resolution, fidelity, region of interest and other characteristics.
- The optional file format describes the meaning of the image and its components in the context of the application.

C. Adaptive SPIHT

The set partitioning in hierarchical trees (SPIHT) [4] is a very suitable method for compression of medical images as it offers a decent compression ratio. The SPIHT [6] method, involves (1) exploitation of the hierarchical structure of the wavelet transform, by using a tree-based organization of the coefficients; (2). Partial ordering of the transformed coefficients by magnitude, with the ordering data not explicitly transmitted but recalculated by the decoder; and (3) ordered bit plane transmission of refinement bits for the coefficient values. The Adaptive SPIHT compression scheme provides selective compression on medical images by compressing the ROI using JPEG2000 and the rest of the image by standard SPIHT, making it energy efficient. It involves following two phases:

(a) Energy efficient SPIHT on non-ROI

This is the region that must be exploited to achieve a desired energy efficient medical image compression. It leads to a fully embedded bit stream with the maximum value coefficients at first and the minimum value coefficients at the end of the stream, making this scheme applicable on the non- ROI image. This is the region which must be exploited to make the compression energy efficient. Discrete wavelet transform is the transform made use of. As this part of the medical image is of no diagnostic importance all the high frequency bands can be completely eliminated and only the low frequency components of the transform level be sent further. The advantage that remains out of doing this is that the compression time, the reconstruction time and peak signal to noise ratio is considerably reduced, along with an enhanced compression ratio.

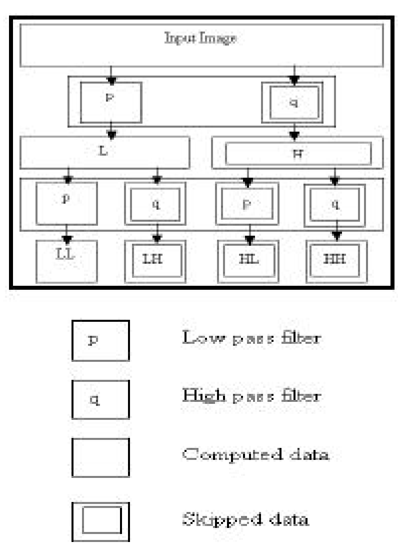

Fig.4. Adaptive SPIHT

b) JPEG2000 on the ROI

The most important information lies in the Region of Interest. Quality after reconstruction is of outmost importance in case of medical images. The JPEG algorithm [12], [14] ensures quality .Power consumptions are greatly ruled by the varying implementations of the JPEG algorithms. Compression here cannot be afforded to be made energy efficient as this will lead to loss of detailing information. As the ROI selected is very small in size, in that case, instead of partitioning the bits into blocks, as for Embedded Block Code for Optimized Truncation (EBCOT), the bits are Huffman [6] or Run length coded directly, after the discrete wavelet transform has been applied. We can afford the decrease in bit rate on account of this for the sake of quality which is compromised by blocking artifacts whenever we go for splitting the image into blocks for any computation. The encoding and decoding computational complexities is drastically reduced as these are extremely simple methods of encoding.

D. JPEG2000 ROI coding through component priority

(a) Overview and coding mechanisms

Most JPEG2000 [13] implementations require four main coding stages to produce a compliant code stream [15]: sample data transformations, sample data coding, rate-distortion optimization, and code stream re-organization. The main operations related to ROI coding in JPEG2000 are the fractional bit plane coding process carried out in sample data coding, and the rate-distortion optimization stage. The JPEG2000's fractional bit plane coder is based on Embedded Block Coding with Optimized Truncation (EBCOT) [16]. The main idea behind this coding paradigm is to code small sets of wavelet coefficients (called code blocks) independently, and to optimally truncate the bit streams generated for these code blocks to form the final code stream. The bit stream generated for each code block can be truncated at the end of each coding pass, which produces several truncation points that can be potentially employed by the rate-distortion optimization stage.

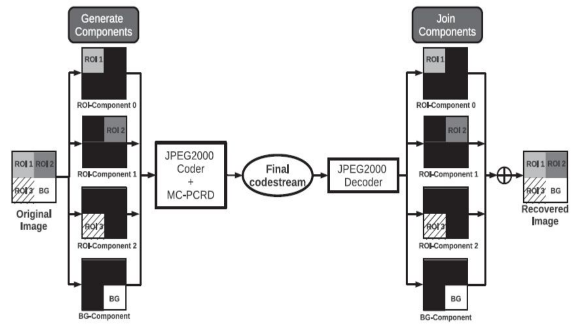

Figure 4. JPEG2000 ROI coding method operations. Two operations are added in coder/decoder pipeline: generate components and join components

IV. Error Metrics

A. PSNR

The objective performance is measured by peak signal-to-noise ratio (PSNR) of the reconstructed image. PSNR measured in decibels (dB) is given by:

PSNR=20*log10 (255/sqrt (MSE)), where the value 255 is the maximum possible value that can be attained by the image signal. Mean square error (MSE) is defined as

$$\frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left[I(x,y) - I'(x,y)\right]^2$$

where M * N is the size of the original image. PSNR is measured in decibels (dB). It has been shown that PSNR is not always an indicator of the subjective quality of the reconstructed image.

B. Correlation

The Correlation between the reconstructed image and the original image is measured by the formula:

$$r_{xy} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{(n-1)s_x s_y} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\ \sqrt{n\sum y_i^2 - (\sum y_i)^2}}.$$

Where x and y are the images, $\bar{x}$ and $\bar{y}$ are the mean of the images, s_x and s_y are the standard deviations of x and y. The coefficient r_{xy} is scaled in the range -1 to 1.

V. Proposed Compression Method

In this research we present the comparison of three different compression techniques. The extraction of region of interest (ROI) is preceded by the comparison, which is divided into the following phases. Phase one- ROI is extracted interactively from the image, dividing the image into two regions, because the radiologists are interested on the relevant areas needed to perform correct diagnosis. Phase two- Original image, ROI and the background are compressed with different compression algorithms, SPIHT, JPEG2000 and Adaptive SPIHT to evaluate the one with highest quality after reconstruction. Phase three- The case is analyzed for images containing multiple ROIs, where the priorities are set by default, in order to recover to them at higher quality than the rest of the image, the background. Compression in the last phase is carried out by implementing JPEG2000 on the ROI because quality after reconstruction is of outmost importance here. All the compression techniques implemented are wavelet based.
The Fig.5.depicts the general methodology implemented in the research work.

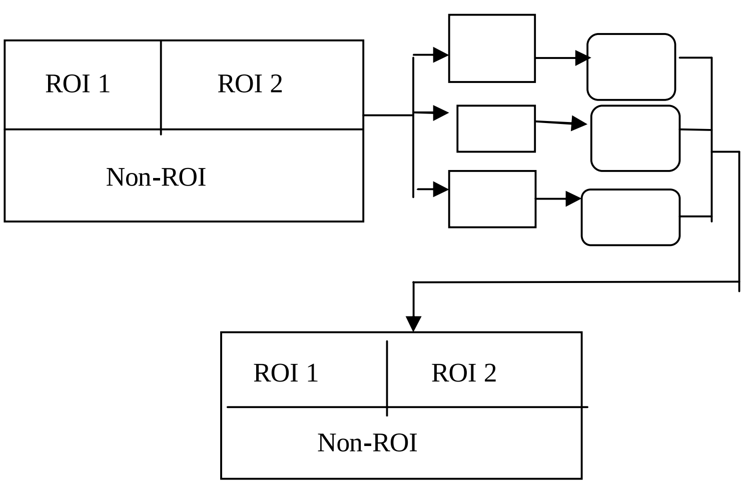

Fig.5. Proposed Methodology

A. Extracting the breast region

An important characteristic in all medical images is that it can be classified into two areas easily. One area is the body part that is subject to diagnosis in the image. Another area is the background with less important information. This work is proposed to select more than one region of interest, according to the priority of the information required. So the first step in the paper is segmenting the image into two regions. One approach is suggested for this. One is the selection of the region of interest by hand and then superimposing the selected pixel matrix on an m*n matrix of zeroes, where m and n refer to the number of horizontal and vertical pixels in the image respectively. The background is left as such with zero values for the selected region.

B. Segmenting the Image data

After choosing the ROI, image is divided into multiple ROIs and Non-ROI. ROIs chosen is not restricted to be of a square or a rectangular region, can be of any arbitrary shape. ROIs need to be encoded with different priorities. ROI priority determines its importance in the image. The ROI with higher priority is compressed at a higher bit-rate than the rest of the ROIs. The Non-ROI usually has a lower priority, which is appeared in the final part of the whole image bit stream. ROIs are sent to the encoder chosen directly. Non-ROI coefficients are sent to another encoder chosen by the user.

C. ROI lossless and lossy compression

Because the extracted breast region contains important diagnosis information, it needs to be compressed losslessly. A set of mammograms is tested with the three major compression algorithms: SPIHT, JPEG2000, and Adaptive SPIHT. The performance evaluation results for the above mentioned error metrics are displayed in the form of graphs: Graph 1, Graph 2, Graph 3, Graph 4, Graph 5, and Graph 6.

D. Multiple arbitrary shape ROI compression

This paper introduces a ROI coding method that is able to prioritize multiple ROIs at different priorities, guaranteeing lossy-to-lossless coding. Region Of Interest (ROI) coding is a prominent feature of some image coding systems aimed to prioritize specific areas of the image through the construction of a codestream that, decoded at increasing bit-rates, recovers the ROI first and with higher quality than the rest of the image. JPEG2000 provides lossy-to-lossless compression and ROI coding, which are especially relevant to the medical community. Table 1 gives the compression ratio comparisons with more than one ROI

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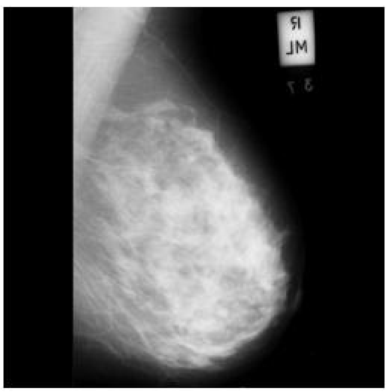
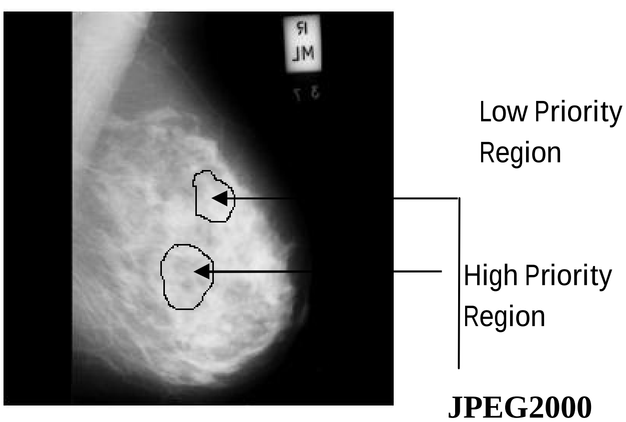
encoded with JPEG2000. The performance is evaluated by means of PSNR and correlation. Fig , shows the reconstructed mammogram. It shows completely the same effect as the original one, which means that the proposed method can achieve quite good compression performance while not bringing any diagnosis information loss.

TABLE1COMPRESSION RATIO COMPARISON

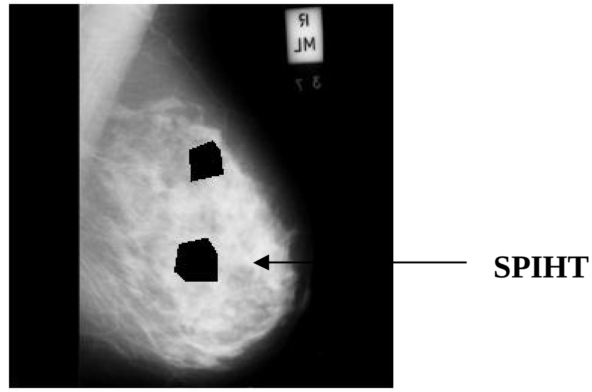
Image(mdb1.bmp)	PSNR	Corr
ROI (1)----- 1.3bpp	54.7535	0.9893
ROI(2) 0.9	52.6815	0.9709
ROI(2) 0.8	51.8834	0.9628



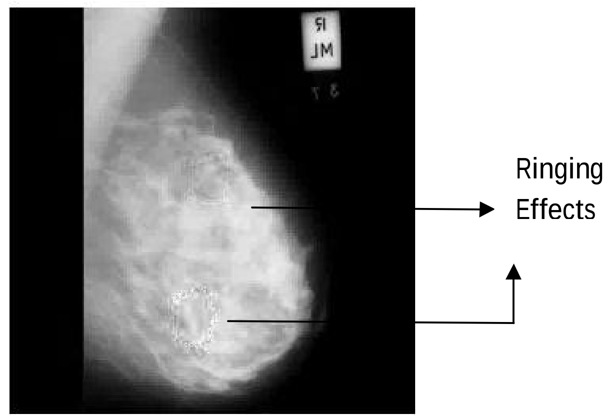
(a) Original Image



(b) Multiple arbitrary shape ROI compression



(c) Non-ROI Compression



(d) Combined Output (Reconstructed Image)

VI. Experimental Results

Different ROI schemes were applied on ultrasound images and the performance was evaluated by PSNR, Time and correlation parameters. The study shows that the time required to encode the ROI is less as compared to the encoding of the whole image with JPEG2000; Figure 6. In Figure 7, the comparison is done over the “time to decode”, in case of JPEG2000. Figure 8 shows that the three different ROI schemes, when applied on the same mammogram result: PSNR performance is highest in case of Adaptive SPIHT. As per the experimental evaluation, Figure 9 shows that Correlation among the two reconstructed images is also conserved in Adaptive SPIHT. The images are compressed at varying bit-rates. This implies that, ROI with a higher priority attains high PSNR, in comparison to the ROI with lower priority, as can be observed in Figure 10. Figure 11 shows that Higher the priority of the ROI, higher is the correlation value.

Comparison of Time to encode on the whole image and the ROI

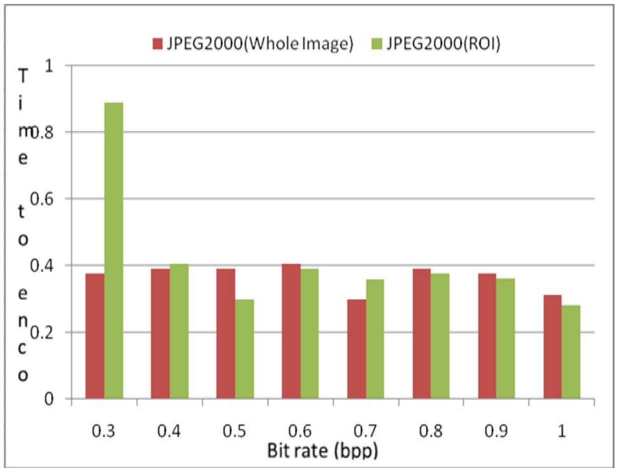


Figure 6

Comparison of Time to decode on the whole image and the ROI

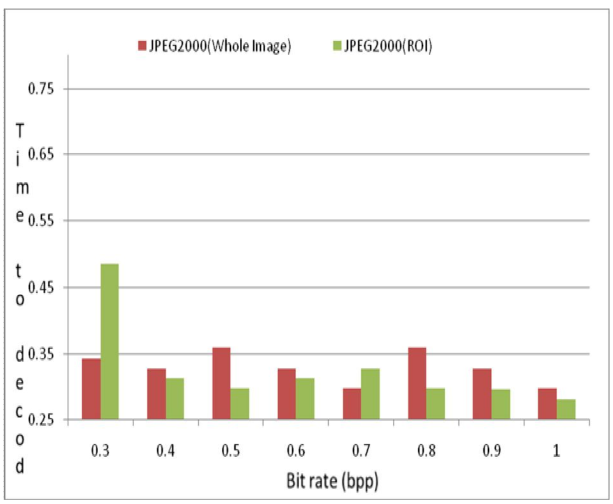


Figure 7

Comparison of PSNR on the ROI and Non-ROI (different ROI schemes)

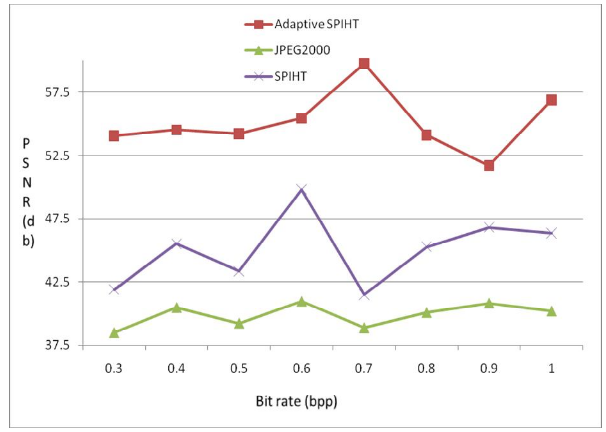


Figure 8

Comparison of Correlation on the ROI and Non-ROI

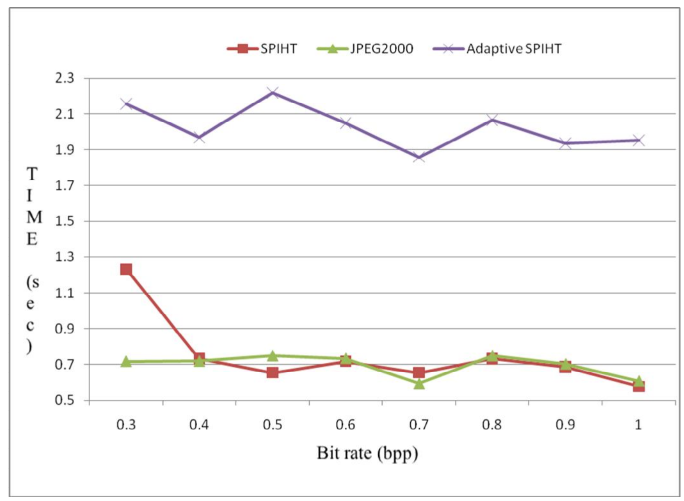


Figure 9

Comparison of PSNR on the higher priority ROI and lower priority ROI

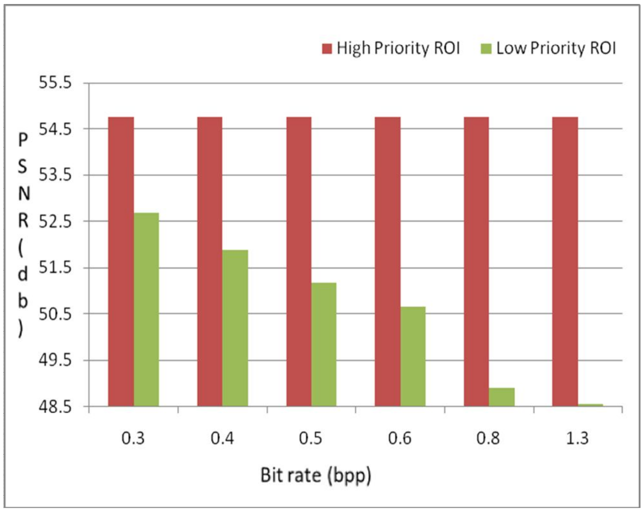


Figure 10

Comparison of Correlation on the higher priority ROI and the lower priority ROI

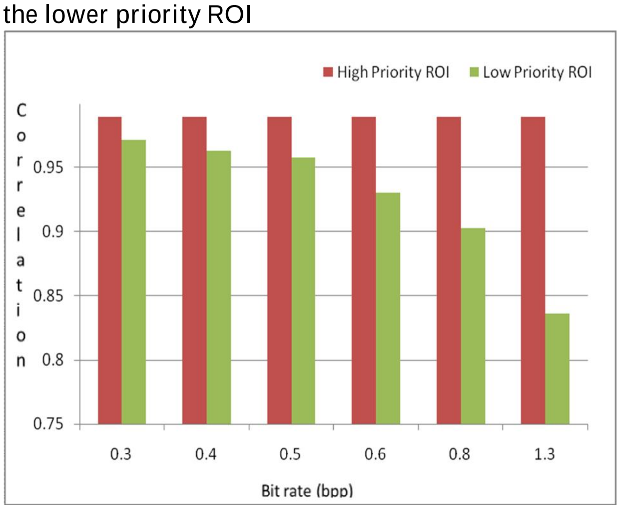


Figure 11

VII. Conclusion

The current generation of digital images (mammograms) is huge and growing and can potentially overflow the storage capacity of medical image centre. In order to reduce the cost of disk space, efficient storage increase the on-line availability of patient data, the loss is necessary and helpful in the longer term for medical images. Compression schemes produce high compression rates if loss of quality is acceptable. However, in most cases physicians may not afford any deficiency in diagnostically high compression rate with good quality in the ROI is thus necessary. From the study we have reached the following conclusions:

- Adaptive SPIHT proves to be the best while compression digital mammograms. The value of PSNR, Correlation and time prove to be the best for the same.
- Region-based coding techniques allow the compression of multiple regions at several quality levels within an image.
- Multiple ROI-coding enables enhanced quality for the many ROIs visible in one single mammogram. The benefits obtained from ROI coding are enomorous.
- JPEG2000 ROI coding mechanism allows the compression of the ROI with highest priority than the rest of the image. The values of PSNR and Correlation justify the same.

Regions with specific interest for performing the diagnosis as determined by the physician are retrieved with high quality factors upon user's request. In this thesis, we concentrate on the integration of the ROI and Non-ROI, along with compressing multiple ROIs at different priorities. Future work can be extended to remove the ringing effects obtained while adding the ROI and Non-ROI of a medical image for integration. The ROI can also be watermarked for security once the bit stream emerges from the encoder. This would prevent tamper and also provide for not only memory and energy efficient but also secure telemedicine.

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