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Multi Scale Multi Directional Region of Interest Based Image Compression Using Non Subsampled Contourlet Transform

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Abstract

An increase in the demand for storing the large archrivals' of medical image data bases and the image data base for surveillance applications paved way for Region of Interest (ROI) based image compression techniques. Different ROI based coding techniques identify fixed shaped regions for compression. However, the real world images are having irregular shaped ROI. So, extraction of directional information along with identification of relevant information along multiple resolutions is very important for performing ROI based compression. Therefore, in this paper a Non Subsampled Contourlet Based ROI Compression for low resolution images is proposed. Furthermore, the ROI is encoded using lossless

encoding techniques for obtaining good resolution and the rest of the image is coded with lossy image compression techniques for obtaining high compression ratio. The proposed algorithm is compared with JPEG2000 standard which uses ROI for compression of images, with arithmetic encoder which is a lossless image compression method and also with SPIHT encoder which is a lossy image compression method.

Keywords: non subsampled contour-let, ROI, Compression

1. INTRODUCTION

With growing demand of various imaging applications, the storage requirements of digital images are growing at an exponential rate. Image coding, storage and transmission through a channel with limited band width, is a very important and active area of development today. Noticeably, image data generally consists of a large amount of redundant information for its representation. Image compression techniques help to reduce the redundancies in raw image data to reduce the storage space and occupancy in channel band width.

In the early days of research, image compression was most commonly used for printing, data storage and telecommunication. However, these days, the applications of image compression have increased many a fold and are being used in applications like fax transmission, satellite remote sensing, High Definition (HD) TV and so on [1].

In medical applications, where there is a huge archival of large number of images, image compression is used for storing information without putting large loads on system servers. Security is one area, where image compression has a major contribution. In this field, image compression is used to greatly increase the efficiency of recording, processing and storage. However, in such applications, it is imperative to determine whether one compression standard would benefit all areas or not. For example, in a video networking or closed circuit TV applications, several images at different frame rates may be required. Also some regions like faces have more importance than rest of the human body [2].

This paper aims at putting focus on such applications, in order to develop an efficient algorithm that provides variable compression standards at different regions to retain the image resolution even after maximum possible compression.

Wavelet transforms gained much popularity because of their suitability for a number of image processing applications including image coding. Both orthogonal and bi-orthogonal wavelets are useful for image compression. Wavelet methods use overlapping transforms with a variable length basis functions. The use of overlapping transforms reduces the blocking artifacts and the multi resolution capability of wavelets provides excellent energy compaction and quality for the de compressed image. The activity in wavelets was initiated by Mortlet's work in geo physical signal processing [3-8].Coifman and Wickeerrhauser proposed an adaptive sub band decomposition using ortho normal filter banks and base comparison for image compression [9]. Likewise many researchers have worked on wavelets for achieving better compression ratios without the quality of the image. However, it is observed by the researchers that wavelet image coders are very sensitive to bit errors and therefore are not suitable for noisy channels [10]. So, now researchers are working on modifying wavelets to be error resilient in noisy channels.

Conventional image compression algorithms introduce distortion in the images as they uniformly code the entire image. Furthermore, discrete wavelet transforms alone are not suitable for identification of arbitrarily shaped regions in the image. So, there is a need for extraction of irregularly shaped regions by providing directionality to discrete wavelet transforms. This paper aims to develop an efficient Region of Interest (ROI) based image compression algorithm which applies variable compression standards at different areas in order to maintain the quality of image even after high compression.

In order to meet the above mentioned problem, the following objectives are performed:

1. Use of Non-subsampled Contourlet (NSCT) transforms for multi resolution analysis in order to analyze the image at all scales of resolution and to estimate the contours of the target in all directions
2. Use of a statistical thresholding in edge detection to rightly identify the target boundaries
3. Use of Arithmetic coding for ROI regions and SPIHT coding for Non ROI regions
4. Comparison of the results of proposed algorithm with state of the art and recent image compression algorithms.

The rest of the paper is organized as follows: Section 2 presents a detailed description of proposed methodology. In section 3 the results obtained for several images using the proposed algorithm are presented. The comparisons of the performance of proposed algorithm with several other techniques are presented in Section 4 and finally section 5 concludes the paper.

2. METHODOLOGY

The block diagram of the Region of Interest Based Image Compression System using Directional Filter Banks is shown in FIGURE1. As shown in FIGURE1, a low bit rate bit map image is taken as input for the proposed methodology. The artifacts of the image are removed by using a suitable filter in the pre-processing stage. The image with enhanced quality is then decomposed into several scales by using NSCT transforms. NSCT is used for identifying the amount of information present at all scales of resolution. For each of the approximate and detailed coefficients obtained along horizontal, vertical and diagonal directions, and to identify the directional frequency.

For a given scale, the direction in which maximum amount of information available would be given by the directional frequency. Now, these directions are considered to be the regions of interest. In order to separate the region of interest from the rest of the image edge detection is done.

A local thresholding scheme which uses statistical methods is considered for edge detection, so that noise pixels are not identified as true edges. After the Region of Interest (ROI) is identified, the ROI is coded with a most popular Arithmetic coding so that information in the ROI is retained. In order to achieve high compression ratios, the rest of the image is coded with Set Partition in Hierarchical Tree (SPIHT) coding.

During decoding arithmetic decoding is done for ROI image and SPIHT decoding is done for the rest of the image. Then both the decoded images are added to get the final de-compressed image with a better Peak Signal to Noise Ratio (PSNR) and high Compression Ratio (CR). The block diagram for decoding using the proposed methodology is shown in FIGURE2.

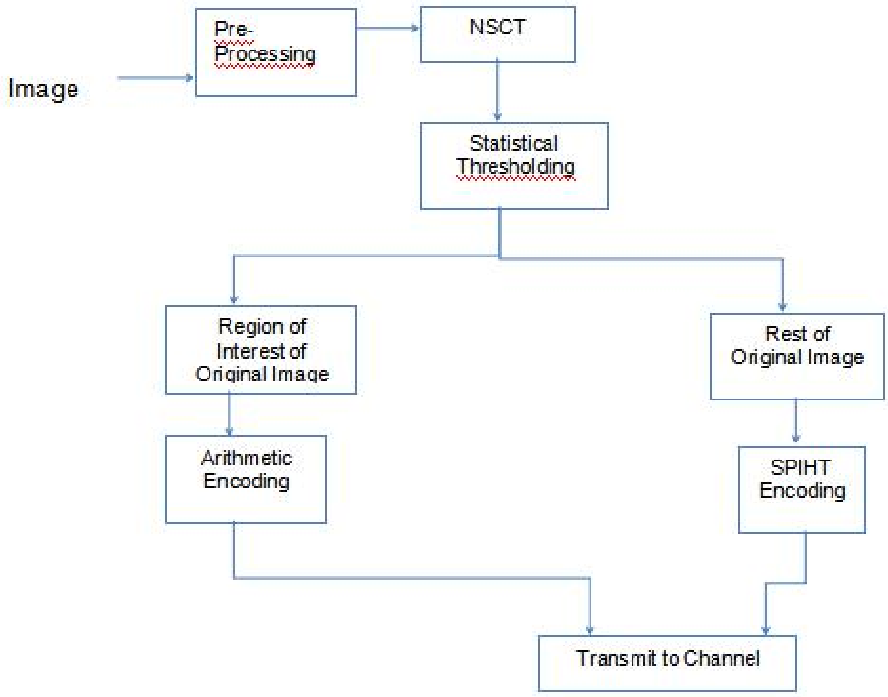


FIGURE 1*:* Block Diagram of Proposed Methodology for Image Encoding

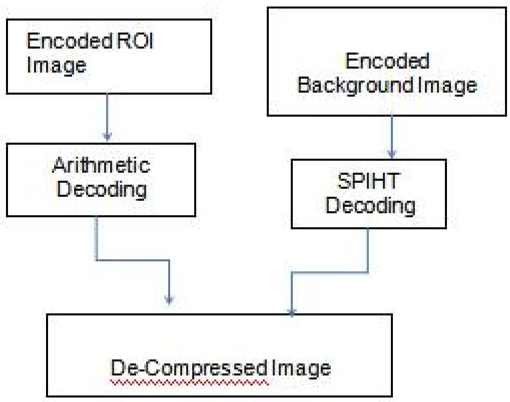


FIGURE 2: Block Diagram of Proposed Methodology for Image Decoding

2.1 Pre-Processing

The purpose of pre-processing in the proposed method is to remove noise from the input image. The challenge for pre-processing in the methodology is to preserve the edges while removing the noise and both the signals carry high frequency information. So, a bilateral filter is used to serve the purpose. The bilateral filter is given by the equation (1).

$$f_{out}(x,y) = \frac{\sum\sum f_{in}(u,v)\exp\left(-\frac{(f_{in}(x,y)-f_{in}(u,v))^2}{2\sigma_r^2}\right)\exp\left(-\frac{((x-u)^2+(y-v)^2)}{2\sigma_d^2}\right)}{\sum\sum \exp\left(-\frac{(f_{in}(x,y)-f_{in}(u,v))^2}{2\sigma_r^2}\right)\exp\left(-\frac{((x-u)^2+(y-v)^2)}{2\sigma_d^2}\right)} \quad (1)$$

$f_{in}(x, y)$=Input Image

(u, v) = Neighborhood points

$f_{out}(x, y)$=output Image

σ_r = Variance of Range

σ_d = Variance of Domain

2.2 Non Sub-Sampled Contourlet Transforms

Contourlet transform is a decomposition algorithm based on Laplacian Pyramids and Directional Filter banks and is used to achieve low redundancy, multi-scale, multi-direction analysis. However, it uses down sampling which causes pseudo-Gibbs phenomena around singularities. So, NSCT is derived from Contourlet transform in order to reduce overlapping spectrum in Contourlet transform process. NSCT contains two shift-invariant parts: one is non-subsampled pyramid (NSP) decomposition that ensures the multi-scale property, the other is non-subsampled DFB (NSDFB) that gives directionality. Since there is the sampling link in NSCT, each directional sub-bank has the same size with original input image. A two level decomposition of the signal using NSCT is shown in FIGURE3

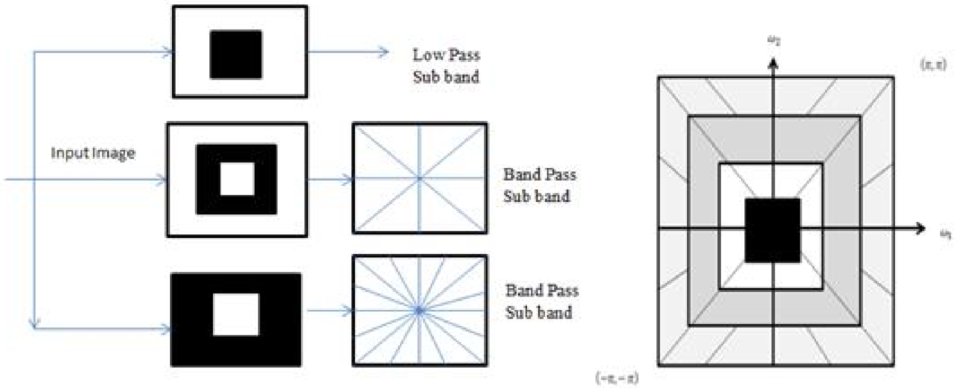


FIGURE 3: Two Level Decomposition using NSCT

Initially, the non-subsampled pyramid structure decomposes 2-D input signal into a high-frequency and low-frequency sub-bands. Then the non -subsampled directional filter bank decomposes the high-frequency sub-band into directional sub-bands and low-frequency sub-band is decomposed into the second level high-frequency sub-band and low-frequency sub-band. Similar decomposition is repeated on the low-frequency sub-band output by NSP structure, thereby achieving multi-scale and multi-direction analysis. Because the multi-scale decomposition and the multi-direction decomposition are independent of each other, the number of direction decomposition on each high-frequency sub-band can be the any positive integer power of 2.

2.3 ROI Detection with Statistical Thresholding

This methodology uses a binary mask for ROI detection. Each pixel in the mask records whether it belongs to part of ROIs. The binary mask is obtained by making use of an edge detection technique, which considers statistical variability of pixels to choose a threshold to identify it as an edge pixel or not. Within a given scale with maximum energy localized in given directions, the said edge detection technique is applied to get the boundaries of the region

2.4 Arithmetic Encoding

The ROI coding is done using Arithmetic coding which is a lossless image compression technique. Arithmetic coding is an entropy coder for lossless compression. It encodes the entire input data using a real interval. The first step in arithmetic coding is to create an interval for each symbol, based on cumulative probabilities. The interval for a symbol is represented as [low, high). For each given input string, the interval of the first symbol is determined and then the remaining intervals are scaled as given by the equation (2)

$$\left.\begin{aligned} \text{New Low} &= \text{Current Low} + \text{Sumn-1}(p)*(H - L) \\ \text{New High} &= \text{Current High} + \text{Sumn}(p)*(H - L) \end{aligned}\right\} \quad (2)$$

2.5 SPIHT Encoding

SPIHT algorithm was introduced by Ameer Said and Pearlman. One of the main features of this coding method is that the ordering data is not explicitly transmitted. Instead it is based on the fact that the execution path of any algorithm is done by the results of the comparisons on its branching points. So, if the encoder and decoder have the same sorting algorithm, then the decoder can duplicate the encoder's execution path if it receives the results of the magnitude comparisons and the ordering information can be recovered from the execution path. In this sorting algorithm we do not need to sort all coefficients but simply selects the coefficients such that $2n<|c_{i,j}|<2n+1$,with 'n' decremented in each pass. Given n, if $c_{i,j}>2n$ then we say that a coefficient is significant, otherwise it is called insignificant. The sorting algorithm divides the set of pixels into $\max_{(i,j)\in T_m}\{|C_{i,j}|\} \geq 2^n$ partitioning subsets Tm and performs the magnitude test. If the decoder receives a 'no' to that answer, the subset is insignificant, and then it knows that all coefficients in Tm are insignificant. If the answer is 'yes', the subset is significant., then a certain rule shared by the encoder and the decoder is used to partition Tm into new subsets Tm,l and the significance test is then applied to the new subsets. This set vision process continues until the magnitude test is done to all single coordinate significant subsets in order to identify each significant coefficient. Thus, this technique offers a very good compression ratio.

Similarly after receiving the encoded signals, arithmetic decoding and SPIHT decoding are done for ROI image and rest of the image respectively.

Considering all the steps mentioned above the proposed Non-Subsampled Contourlet Based Region of Interest Compression (NSCTRC) algorithm is described below:

NSCTRC Algorithm

Input: An uncompressed image of size MxN

Step 1: Preprocessing

The noise in the input image is filtered using an appropriate Bi lateral filter which removes noise but retains the high frequency edge information

Step2: Multi Scale and Multi Directional Decomposition using NSCT

The image is decomposed into several levels) in order to determine the amount of information present at each scale of resolution and the details of the information present along the eight directions of the image are extracted using the NSCT

Step3: Edge Detection using Statistical Thresholding

An edge detection scheme that uses a statistical Thresholding is applied on each of the eight directional sub images and all the edges are integrated to get the final edge map

Step4: Coding ROI and rest of the image

The region of interest is coded using arithmetic coding and the rest of the image is coded using the most famous SPIHT algorithm. Finally, now the image is ready for decoding. The decoding is just the reverse of encoding. The next section presents the results obtained for image compression using NSCTRC algorithm

3. RESULTS

Many general images and low resolution images are considered for experimentation. The processing of the images is done on an intel core i3 processor. The reason for selecting low resolution images is that all the existing state of the art and recent coding techniques fare very efficiently in coding the high resolution images. But their efficiency diminishes when low resolution images are considered. So, the concept of ROI based coding is much useful for such images where a good balance should be made between retaining the quality of the image and achieving high compression ratios. The Results are shown for three different sets of images under ideal conditions and under noisy conditions. The three different sets of images considered are:

- Images with single ROI
- Images with two ROIs
- Images with multiple ROIs

3.1. Results for Images with Single ROI

A Camel image shown in FIGURE 4(a) is taken into consideration as an image with single ROI. The monochrome image of the camel is shown in FIGURE4(b). The directional sub images of the camel obtained after applying NSCT are shown in FIGURE5.

(a) (b)

FIGURE4: (a) Camel Image (b) Monochrome Image of Camel

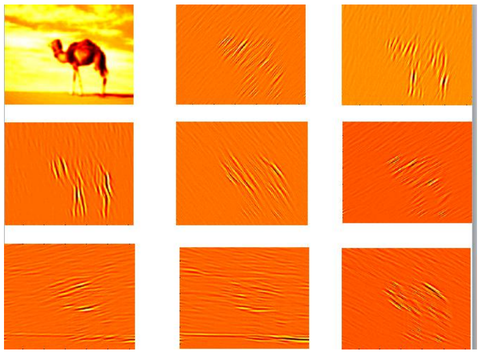


FIGURE5: Multi-scale Multi-directional Sub-bands of Camel Image

The sub-band images give the information the presence of maximum information in a given direction. The region of interest is identified from these sub-bands by detecting the boundary of ROI by making use of an edge detection that uses statistical thresholding. The edge map thus obtained is shown in FIGURE6(a).The extracted ROI from the edge map is shown in FIGURE 6(b) and the rest of the image is shown in FIGURE6(c).

(a) (b) (c)

FIGURE6: (a) Edge Detection (b) ROI of Camel (c) Rest of Image of Camel

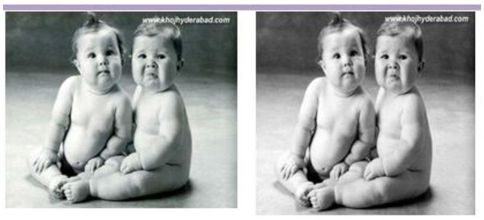
The final image obtained after decoding is shown in FIGURE7(b) and is comparable with the original image shown in FIGURE7(a).

(a) (b)

FIGURE7: (a) Original Image (b) Decoded Image obtained from NSCTRC Algorithm

3.2. Results for Images with Two ROIs

The next image taken into consideration is a "Babies image shown in FIGURE8 (a) which has two ROIS. Its corresponding monochrome image is shown in FIGURE8 (b).



(a) (b)

FIGURE8: (a) Babies Image (b) Monochrome Image of Babies

The sub-images obtained after applying NSCT on Babies image is shown in FIGURE9.

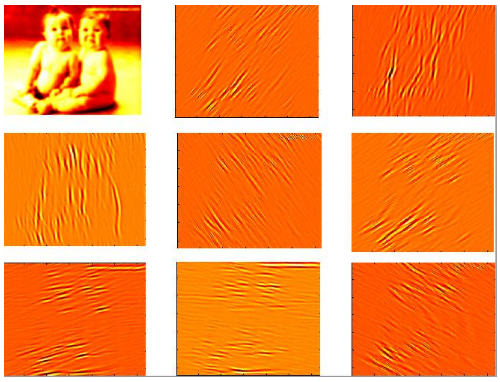


FIGURE9: Multi-scale Multi-directional Sub-bands of Babies Image

The sub-band images give the information the presence of maximum information in a given direction. The region of interest is identified from these sub-bands by detecting the boundary of ROI by making use of an edge detection that uses statistical thresholding. The edge map thus obtained is shown in FIGURE10(a).The extracted ROI from the edge map is shown in FIGURE 10(b) and the rest of the image is shown in FIGURE10(c).

FIGURE10: (a) Edge Detection (b) ROI of Babies (c) Rest of Image of Babies

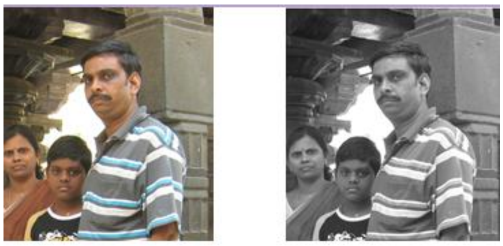
The final image obtained after decoding is shown in FIGURE11 (b) and is comparable with the original image shown in FIGURE11 (a).

(a) (b)

FIGURE11: (a) Original Image (b) Decoded Image obtained from NSCTRC Algorithm

Results for Images with Multiple ROIs

The next image taken into consideration is a “Family” image shown in FIGURE12 (a) which has two ROIS. Its corresponding monochrome image is shown in FIGURE12 (b).



(a) (b)

FIGURE12: (a) Familys Image (b) Monochrome Image of Family

The sub-images obtained after applying NSCT on Family image is shown in FIGURE13.

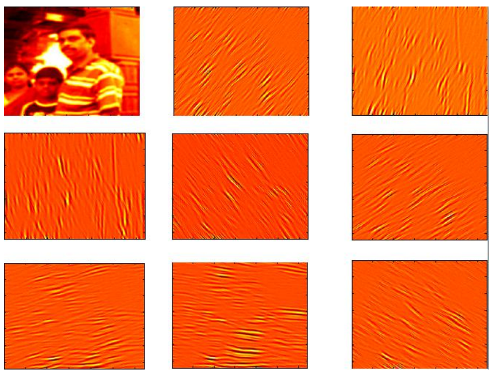


FIGURE13: Multi-scale Multi-directional Sub-bands of Family Image

The sub-band images give the information the presence of maximum information in a given direction. The region of interest is identified from these sub-bands by detecting the boundary of ROI by making use of an edge detection that uses statistical thresholding. The edge map thus obtained is shown in FIGURE14(a).The extracted ROI from the edge map is shown in FIGURE 14(b) and the rest of the image is shown in FIGURE14(c).

FIGURE14: (a) Edge Detection (b) ROI of Family (c) Rest of Image of Family

The final image obtained after decoding is shown in FIGURE15 (b) and is comparable with the original image shown in FIGURE15 (a).

(a) (b)

FIGURE15: (a) Original Image (b) Decoded Image obtained from NSCTRC Algorithm

Results for Low Resolution Images

The proposed algorithm is tested for its robustness by applying it on low resolution images. The reason for selecting low resolution images is that all the existing state of the art and recent coding techniques fare very efficiently in coding the high resolution images. But their efficiency diminishes when low resolution images are considered. So, the concept of ROI based coding is much useful for such images where a good balance should be made between retaining the quality of the image and achieving high compression ratios.

Initially, the “Puppy” image shown in FIGURE 16 (a) is taken into consideration. The edge map of the ROI after segmenting the background is shown in FIGURE16 (b), the results obtained by applying lossless compression to ROI lossy compression to background and the final compressed image obtained after combining both lossless and lossy compressed images are shown from FIGURE16(c) to FIGURE16 (e) respectively.

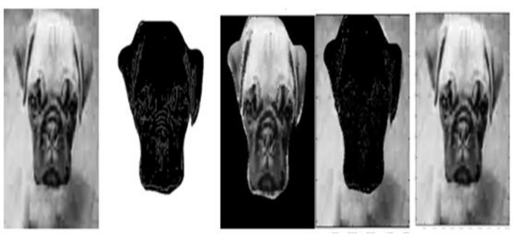


FIGURE16: (a) Low Resolution Puppy Image (b) ROI of Puppy Face (c) Lossless ROI Compression (d) Lossy Background Compression (e) Final De compressed Image

From the images it is observed that the visual quality of the original image and the final de compressed image is more or less the same.

Then, the low resolution dent image shown in FIGURE17 (a) is taken into consideration.

The dent image is a very low resolution image. It is essential to keep all the lines inside the dent because they are the most important parts for a dentist to identify the depth of the root and the extent to which the canal has to be filled while doing a root canal treatment. Therefore, the image with root and their shape is taken as ROI which is shown in FIGURE 17(b) and the rest of the image is shown in FIGURE 17 (c). Finally the decoded image using the MDWR algorithm is shown in FIGURE 17(d).

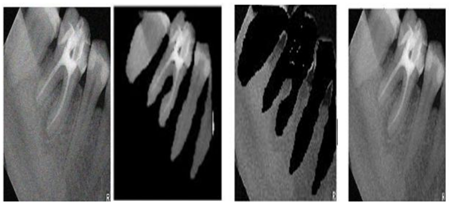


FIGURE17: (a) Dent Image (b) ROI of Dent Image (c) Background of the Dent Image (d) Final Decoded Image using NSCTRC Algorithm

Now, the Lungs image shown in FIGURE18 (a) is taken into consideration.

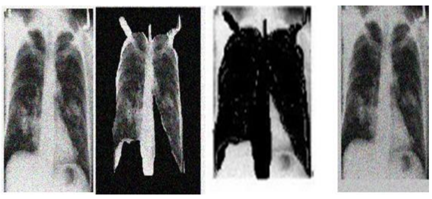


FIGURE18: (a) Lungs Image (b) ROI of Lungs Image (c) Rest of the Image (d) Final De compressed Image using NSCTRC Algorithm

The ROI of the Lungs image is shown in FIGURE18 (b), the rest of the image is shown in FIGURE18 (c). The finally decompressed image obtained after applying MDWR algorithm is shown in FIGURE18 (d).

From the above figures, it is observed that the ROI is having the quality as good as the original image and the reduction in quality of the background image is also not dominantly noticeable. The final de compressed image is visibly showing the same quality as the original image in the ROI.

The results obtained by applying the proposed algorithm to several categories of images are presented in this section. The next section discusses the comparisons of the performance of the proposed algorithm with the state of the art standard compression algorithms and the recent techniques in image compression.

4. Comparisons

Initially, the Subbu image shown in FIGURE19 (a) is taken into consideration for comparison.

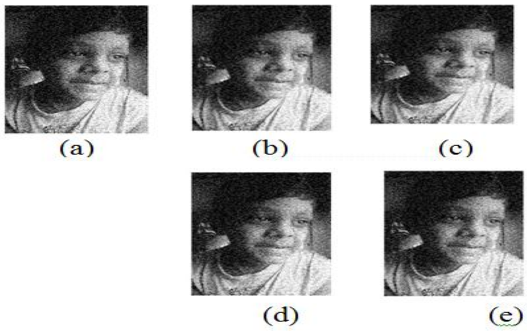


FIGURE19: (a) Original Image of Subbu, Reconstructed images of Subbu using(b) SPIHT Encoding (c) Arithmetic Coding (d) JPEG2000 (e) NSCTRC Method

It is also a low contrast low resolution image with lot of Gaussian and speckle noise. The image is decoded by using all the coding techniques discussed above and the results are shown from FIGURE19 (b) to FIGURE19 (e) respectively. The boundary artifacts of JPEG 2000 coding are more visible along the cheek lines of Subbu's face in the results which are not found in the results obtained from proposed NSCTRC algorithm

Then, the Mammogram image shown in FIGURE20 (a) is taken into consideration for comparison. It is also a low contrast low resolution image with lot of Gaussian and speckle noise. The image is decoded by using all the coding techniques discussed above and the results are shown from FIGURE20 (b) to FIGURE20 (e) respectively.

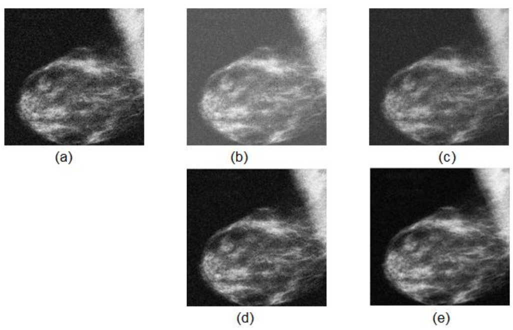


FIGURE 20: (a) Original Image of Mammogram, Reconstructed images of Mammogram using: (b) SPIHT Encoding (c) Arithmetic Coding (d) JPEG2000 (e) NSCTRC Method

The comparisons are also made with respect to quantitative evaluation. All the algorithms are compared for their performance efficiency by making use of the parameters like PSNR (dB), Compression Ratio and Percentage of Compression. The results of the comparison are given in Table I. The parameters mentioned above are described by the equations (3) to (5).

$$CR=\frac{Input\ File\ Size\ (Bytes)}{Output\ File\ Size\ (Bytes)} \tag{3}$$

$$\text{Compression Ratio in Percentage } R=\left(1-\frac{1}{CR}\right)100 \tag{4}$$

$$PSNR=10\log_{10}\frac{(L-1)^2}{\frac{1}{MN}\Sigma\Sigma\left[E(x,y)-f(x,y)\right]^2} \tag{5}$$

Where CR is the compression Ratio, L is the number of gray levels in the image, E(x, y) is the output image and f(x, y) is the input image

M is the number of pixels along the horizontal direction and N is the number of pixels along the vertical direction.

PSNR is the Peak Signal to Noise Ratio measured in decibels.

Table I: Performance Evaluation of NSCTRC Algorithm

Coder	Image	Compression Ratio(CR)	CR in Percentage	Bit rate(bpp)	PSNR(dB)
SPIHT	Camel	15:1	93.3	0.53	20.0992
NSCTRC		**16.2:1**	**93.82**	**1.633**	**24.12**
Arithmetic		1.14:1	12.28	6.95	24.3214
JPEG2000		16.2:1	93.82	0.49	21.1056
SPIHT	Babies	7.85:1	87.26	1.01	23.2746
NSCTRC		**9.23:1**	**89.16**	**1.3**	**20.8364**
Arithmetic		1.04:1	3.84	7.2	25.6342
JPEG2000		9.65:1	89.63	0.82	24.6987
SPIHT	Family	7.8:1	87.17	1.02	18.2132

NSCTRC		**12.4:1**	**91.93**	**0.64**	**25.9603**
Arithmetic		1.34:1	25.37	5.95	23.6541
JPEG2000		8.2:1	87.8	0.98	21.6998

From the evaluation it is understood that the quality of the image obtained by NSCTRC algorithm is better than the SPIHT coder and almost the same as the JPEG2000. Furthermore, the compression ratio achieved by the NSCTRC algorithm is comparable with JPEG 2000 and SPIHT and very much better than the Arithmetic coding. So, the aim to attain a good quality image with a better compression ratio is achieved by NSCTRC algorithm when it is applied on Family image which is having multiple ROIs.

Graphs are also plotted to illustrate the performance of the NSCTRC algorithm w. r. t above mentioned parameters and are shown in Fig.21

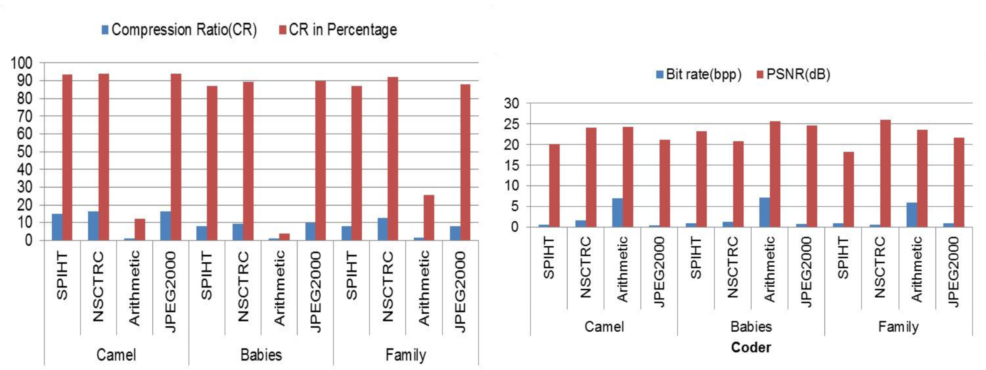


FIGURE 21: Objective Evaluation

5. Conclusion

A new ROI based image compression technique that uses directional filter banks with multiple resolutions is presented. An efficient method for automatic region of interest is discussed. A lossless compression scheme is applied on region of interest and a lossy image compression is done for the rest of the image. The performance of the proposed method is compared against popular lossless compression scheme like Arithmetic coder, lossy compression technique like SPIHT and another ROI based image compression like JPEG2000. The performance of the proposed scheme is found to be better when compared to other algorithms

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