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DICOM Image Compression for Telemedicine based on Region of Interest (ROI)

[1]K.Gopi, [2]K.M.Hemambaran, [3]T.Ramashri,

[1] Assistant professor, Department of E.C.E, SITAMS, Chittoor, Andhra Pradesh, India.
[2]Assistant professor, Department of E.C.E, SITAMS, Chittoor, Andhra Pradesh,
[3]Professor, Department of E.C.E, S.V.University, Tirupati, Andhra Pradesh, India

Abstract: **-- In medical imaging due to increase in demand of storing and transferring the medical images results in need of sufficient memory and transmission bandwidth. Computed Tomography (CT), Magnetic Resonance Image (MRI) procedures produces prohibitive amounts of data, hence compression was introduced in the medical field to renovate these issues. Due to high quantity of information contained in the image, reducing it has become a necessity especially in the medical domain. There exist several compression methods in image processing both lossy and lossless compression. In medical applications Region of Interest (ROI) based compression is preferred to enhance the compression efficiency for transmission and storage. In some areas in medicine, it may be sufficient to maintain high image quality only in the region of interest, i.e., diagnostically important regions, but the cost of a wrong interpretation are high. Due to the reason that in medical filed the diagnostically important region should be compressed with better quality than background. Hence, Region Based Coding (RBC) technique is significant for medical image compression and transmission. Lossless compression schemes with secure transmission play a key role in telemedicine applications that help in accurate diagnosis and research. Block Truncation Coding (BTC) is used for lossy Compression technique and for lossless scalable RBC for Digital Imaging and Communications in Medicine (DICOM) images based on Haar Transform and with distortion limiting compression technique for other regions in image. A detailed analysis is carried out on the basis of parameters like compression ratio (CR), mean square error (MSE) and peak signal to noise ratio (PSNR).**

Keywords:-- **Block Truncation Coding (BTC), Digital Imaging and Communication in Medicine(DICOM), Region of Interest (ROI), Integer wavelet transform(IWT), Mean Square Error (MSE), Compression Ratio(CR), Peak signal to noise ratio(PSNR).**

I. INTRODUCTION

Digital image processing refers processing of the image in digital form. Modern cameras may directly take the image in digital form but generally images are originated in optical form. They are captured by video cameras and digitalized. The digitalization process includes sampling, quantization. Then these images are processed by the five fundamental processes, at least any one of them, not necessarily all of them.

In virtually all image processing applications, however, the goal is to extract information from the image data. Obtaining the information desired may require filtering, transforming, colouring, interactive analysis, or any number of other methods.Now a days medical image processing plays an important role in wide range of applications, especially when we scan an image and we want to transmit the image or to store the image compression plays an important role. While compressing the image the diagnosed part of the image such as tumor or cancer cells should be compressed without loss of information. For medical images, only a small portion of the image might be diagnostically useful, but the cost of a wrong interpretation is high. Lossless compression schemes with secure transmission play a key role in telemedicine applications that help in accurate diagnosis and research. hence the project is aimed to reduced the file size without loss of information especially in the region of interest part.

Basic concept of ROI is introduced due to limitations of lossy and lossless compression techniques. For lossless compression technique the CR is approximately 25% of original size, where as for lossy the CR is much higher but there is loss in the data. Hence, there is a need of some hybrid technique which will take care of diagnostically important part (ROI) as well as will provide high CR.

II. FUNDAMENTALS OF IMAGE COMPRESSION

The term data compression refers to the process of reducing the amount of data required to represent a given quantity of information. A common characteristic of most images is that the neighbouring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the image. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source (image/video). Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS).

It is not an abstract concept but a mathematically quantifiable entity. If n1 and n2 denote the number of information-carrying units in the two data sets that represent the same information, the relative data redundancy RD of the first data set (the one characterized by n1) can be defined as

$$R_D = 1 - 1/C_R \quad (1)$$

Where CR, commonly called the compression ratio, is

$$CR = n1/n2 \quad (2)$$

For the case n2 = n1 and RD = 0, indicating that (relative to the second data set) the first representation of the information contains no redundant data.When n2<< n1. CR -> ∞ and RD ->1, implying significant compression and highly redundant data. When n2 >> n1, CR ->0and RD -> -∞, indicating that the second data set contains much more data than the original representation.

Generally CR =10(10:1) defines that the first data set has 10 information carrying units for every 1 unit in the second or compressed data set. Thus the corresponding redundancy of 0.9 means 90 percent of the data in the first data set is redundant with respect to the second one.In order to be useful, a compression algorithm has a corresponding decompression algorithm that reproduces the original file once the compressed file is given. There have been many types of compression algorithms developed. These algorithms fall into two broad types, lossless algorithms and lossy algorithms. A lossless algorithm reproduces the data exactly same as the original one. A lossy algorithm, as its name implies, loses some data. Data loss may be unacceptable in many applications. For example, text compression must be lossless because a very small difference can result in statements with totally different meanings. There are also many situations where loss may be either unnoticeable or acceptable.

Benefits of Compression

a)It provides a potential cost savings associated with sending less data over switched telephone network where cost of call is really usually based upon its duration. It not only reduces storage requirements but also overall execution time.

b)It also reduces the probability of transmission errors since fewer bits are transferred.

c)It also provides a level of security against illicit monitoring.

Large amount of image data is produced in the field of medical imaging in the form of Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Ultrasound Images, which can be stored in picture archiving and communication system (PACS) or hospital information system. A medium scale hospital with above facilities produces on an average 5 GB to 15 GB of data. So, it is really difficult for hospitals to manage the storing facilities for the same. This is significant for telemedicine scenario due to limitations of transmission medium in Information and Communication Technology (ICT) especially for rural area.

Integer Wavelet Transform

The Integer Wavelet Transform (IWT) is used to have lossless processing. The wavelet transform (WT), in general, produces floating point coefficients. Although these coefficients can be used to reconstruct an original image perfectly in theory, the use of finite precision arithmetic and quantization results in a lossy scheme.

Recently reversible integer wavelet transform has been introduced. Lifting provides an efficient way to implement the Discrete Wavelet Transform (DWT) and the computational efficiency of the lifting implementation can be up to 100% higher than the traditional direct convolution based implementation. Lifting allows simple inverse transform of the same complexity as the forward one. Reversible IWT is

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composed of the elementary operations of the forward one, taken in reverse order.

The advantages of IWT are
(i) Faster calculation with respect to traditional DWT.
(ii) Allows a fully in-place calculation of the wavelettransform, no need of temporary memory.
(iii) Generates only integer number, low computational complexity as compared to DWT whichgenerates floating point numbers.

SPIHT

Set partitioning in hierarchical trees (SPIHT)is an image compression algorithm that exploits the inherent similarities across the sub-bands in a wavelet decomposition of an image.The SPIHT method is not a simple extension of traditional methods for image compression, and represents an important advance in the field. The method deserves special attention because it provides the following:

- Highest Image Quality
- Progressive image transmission
- Fully embedded coded file
- Simple quantization algorithm
- Fast coding/decoding
- Completely adaptive
- Lossless compression
- Exact bit rate coding
- Error protection

❖ ***Disadvantages of Existing System***

- For well-known lossless compression technique the compression ratio is approximately 25% of original size.
- For Lossy encoders, the compression ratio is little bit higher, but there is loss in the data.
- Storage of medical images is generally problematic because of the requirement to preserve the best possible image quality which is usually interpreted as a need for lossless compression.
- Lossy compression schemes are not generally used. This is due to possible loss of useful clinical information which may influence diagnosis.

III. EXISTING METHODOLOGIES

To understand the proposed method, the related works have to be explained. Cziho.A has proposed a vector quantization scheme combined with regions of interest. The input image is to be segmented in to regions and a separate codebook is used for each region. This permits to create codebooks with representative codeword and to obtain good reconstruction quality in relevant zones while reinforcing compression in less important regions. The selected approach is tested on ultrasound images which shown to be very promising

Ujjwal Maulik [17] has proposed a Genetic algorithm which has been found to be effective in medical image segmentation. The problem in medical image segmentation arises due to poor image contrast and artifacts that result in missing tissue boundaries. The resulting search space is therefore noisy with a multitude of local optima. This algorithm brings out considerable flexibility into the segmentation procedure and attempt has been made to review the major application of GAS to the domain of medical image segmentation.

Adrian Munteanu has Proposed a new wavelet based compression technique that exploits the intra band dependies and uses a quad tree based approach to encode the significance maps. The algorithm produces a lossless compression data stream and permits region of coding. The algorithm suits well in telemedicine applications where handling of large image sets over networks with limited or variable bandwidth is required

Chakrapni et al.[18] have applied the technique of genetic algorithm for fractal image compression. This algorithm reduces the search complexity of matching between domain block and range block. The draw back of fractal image compression is that it involves more computational time due to global search. Hence genetic algorithm has been proposed to improve the computational time at an acceptable quality of decoded image. The results have showed that Compare to traditional exhaustive method the Genetic Algorithm was better.

Lavanya [6] has proposed a method to preserve quality in region of interest (ROI).The image is divided in to primary region, secondary region and background region. The two types of compression carried over here are both lossy and lossless. Huffman coding is applied over primary region, The SPIHT algorithm applied over

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Vol 4, Issue 3, March 2017

the secondary region and background. This method preserves quality in region of interest while allowing lossy encoding of other region apart from region of interest. This technique will reduce the storage space and transmission cost and obtains good quality in region of interest.

Doukas[16] Picture archiving communication systems(PACS) application designed for viewing DICOM compliant medical images using wavelet compression ROI coding support is been discussed .He proposed a wavelet transform that has been considered to be a highly efficient technique of image compression resulting in both lossless and lossy compressed images of great accuracy enabling its use on medical images..

G. Vallatha [7]has proposed a hybrid compression model for efficient transmission of medical image using lossless and lossy coding for telemedicine application. As the storage space demand in hospitals is increasing compression of medical images is the need of the hour. Region based coding technique is substantial for medical image compression as only a small part should be diagnosed. To achieve high compression ratio lossless and lossy compression is significant .this paper presents a method of employing both method s integer wavelet transform and the SPHIT algorithm helps to reconstruct the medical image up to the desired quality. Maintaining the Integrity of the Specifications

IV.PROPOSED METHOD

This project discuss about the compressing of ROI part in the medical images. The proposed lossless scalable RBC for Digital Imaging and Communications in Medicine (DICOM) images based on Integer Wavelet Transform (IWT) and with distortion limiting compression technique for other regions in image. User can select ROI of any arbitrary shape. ROI is compressed with lossless version of compression technique such as Haar transform while Non-ROI is compressed by BTC algorithm used after wavelet transform. Wavelet-based techniques are the latest development in the field of image compression. It offers multi-resolution capability that is not available in any of the other method.

Methodology & Implementation

Large amount of image data is produced in the field of medical imaging in the form of Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Ultrasound Images, which can be stored in picture archiving and communication system (PACS) or hospital information system. A medium scale hospital with above facilities produces on an average 5 GB to 15 GB of data. So, it is really difficult for hospitals to manage the storing facilities for the same. This is significant for telemedicine scenario due to limitations of transmission medium in Information and Communication Technology especially for rural area

METHODOLOGIES

- RGB to GRAY Conversion
- Background Removal
- Segmentation
- Compression
- Filtering
- Decompression
- Reconstruction
- Performance Calculation

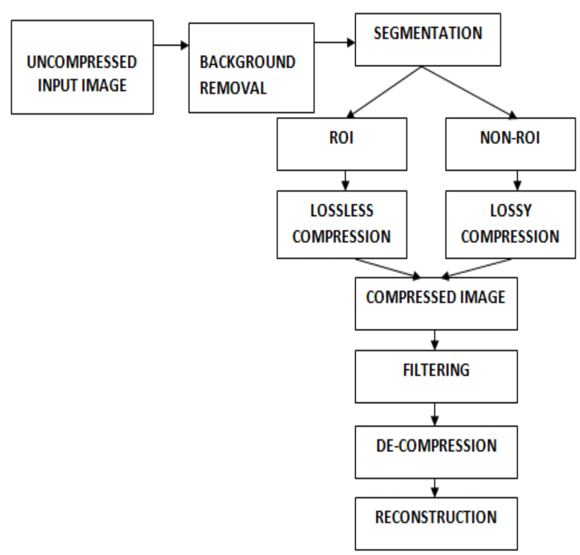

Fig 2: Block Diagram of Proposed Method

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Vol 4, Issue 3, March 2017

- ***RGB to Gray Conversion***

The original image is in an uncompressed format and that the pixel values are within [0, 255], and denote the numbers of rows and columns as N_1 and N_2 and the pixel number as ($N=N_1 \times N_2$). The Input image is converted into grayscale if the given input is in color form.

- ***Background Removal***

The Background portions of the given image are completely removed and hence it will be appear in black color. The foreground regions will be visible. This process is known as background removal.

- ***Segmentation***

The background removed image was given as the input and the edges of the foreground are detected using edge detection techniques. Then by using the thresholding technique the Region of Interest (ROI) portions are segmented. Hence the remaining portion such as Non-ROI part are also segmented by subtracting the background removed image with the ROI part. Hence the ROI and the Non-ROI part are segmented and classified

- ***Cropping***

From the input image, the required portion can also be cropped if needed and the cropped image can be used for further processing.

- ***Compression***

The Segmented/Classified ROI and the Non-ROI part are compressed using the Lossless and Lossy compression techniques respectively. The compression techniques such as Block Truncation Coding (BTC), SPIHT etc., are used. In existing, we can only use the Grayscale image, but here in our proposed methodology we can use color images as an input and the compression can be done for the color image and the compressed output is also obtained in color form.

❖ *Haar Transform For lossless Compression*

The family of N Haar functions $h_k(t)$ are defined on the interval $0 \leq t \leq 1$. The shape of the Haar function, of an index *k*, is determined by two parameters: *p* and *q*, where

$$k = 2^p + q - 1 \qquad (3)$$

and k is in a range of $k = 0, 1, 2, \cdots, N-1$.

When $k = 0$, the Haar function is defined as a constant $h_0(t) = 1/\sqrt{N}$; when $k > 0$, the Haar function is defined as

$$h_k(t) = \frac{1}{\sqrt{N}} \begin{cases} 2^{p/2} & (q-1)/2^p \leq t < (q-0.5)/2^p \\ -2^{p/2} & (q-0.5)/2^p \leq t < q/2^p \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

From the above equation, one can see that p determines the amplitude and width of the non-zero part of the function, while q determines the position of the non-zero part of the Haar function

- ***The Haar Matrix***

The discrete Haar functions formed the basis of the Haar matrix **H**

$$\mathbf{H}_{2N} = \begin{bmatrix} \mathbf{H}_N \otimes [1,1] \\ \mathbf{I}_N \otimes [1,-1] \end{bmatrix} \qquad (5)$$

$$\mathbf{H}(0) = 1$$

Where

$$\mathbf{I}_N = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix} \qquad (6)$$

and $\otimes$ is the Kronecker product. The Kronecker product of $\boldsymbol{A} \otimes \boldsymbol{B}$, where $\boldsymbol{A}$ is an $m \times n$ matrix and $\boldsymbol{B}$ is a $p \times q$ matrix, is expressed as

$$\boldsymbol{A} \otimes \boldsymbol{B} = \begin{bmatrix} a_{11}B & \cdots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{bmatrix} \qquad (7)$$

The Haar matrix is real and orthogonal, i.e.,

- $H = H^*$
- $H^{-1} = H^T$, i.e., $H^T H = I$

- ***The Haar Transform***

The Haar Transform (HT) is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average (approximation) or trend and the other is known as difference (detail) or fluctuation.

The Haar transform $HT^n(f)$ of an *N*-input function $X^n(f)$ is the 2^n element vector

$$HT^n(f) = \mathbf{H}^n X^n(f) \quad (8)$$

The Haar transform cross multiplies a function with Haar matrix that contains Haar functions with different width at different location.

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ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 4, Issue 3, March 2017

In 1909 Haar introduced the Haar wavelet theory. A Haar wavelet is the simplest type of wavelet. In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform. The mathematical prerequisites will be kept to a minimum indeed; the main concepts can be understood in terms of addition, subtraction and division by two. We also present a linear algebra implementation of the Haar wavelet transform, and mention important recent generalizations. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two subsignals of half its length.
The Haar wavelet transform has a number of advantages:

- It is conceptually simple and fast
- It is memory efficient, since it can be calculated in place without a temporary array.
- It is exactly reversible without the edge effects that are a problem with other wavelet transforms.
- It provides high compression ratio and high PSNR (Peak signal to noise ratio).
- It increases detail in a recursive manner.

❖ Block Truncation Coding

Block Truncation Coding is a lossy image compression technique .It is a simple technique which involves less computational complexity. BTC is a recent technique used for compression of monochrome image data. It is one-bit adaptive moment-preserving quantizer that preserves certain statistical moments of small blocks of the input image in the quantized output.

The original algorithm of BTC preserves the standard mean and the standard deviation. The statistical overheads Mean and the Standard deviation are to be coded as part of the block. The truncated block of the BTC is the one-bit output of the quantizer for every pixel in the block. It preserves the higher mean and lower mean of the blocks and use this quantity to quantize output.

In this scheme, the image is divided into non overlapping blocks of pixels. For each block, threshold and reconstruction values are determined. The threshold is usually the mean of the pixel values in the block. Then a bitmap of the block is derived by replacing all pixels whose values are greater than or equal (less than) to the threshold by a 1 (0). Then for each segment (group of 1s and 0s) in the bitmap, the reconstruction value is determined. This is the average of the values of the corresponding pixels in the original block.

Block Truncation Coding (BTC) is a well-known compression scheme proposed for the grayscale images. It was also called the moment-preserving block truncation because it preserves the first and second moments of each image block.

The BTC algorithm involves the following steps:

• **Step1:** The given image is divided into non overlapping rectangular regions. For the sake of simplicity the blocks were let to be square regions of size m x m.

• **Step 2:** For a two level (1 bit) quantizer, the idea is to select two luminance values to represent each pixel in the block. These values are the mean *x* and standard deviation σ

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (9)$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x}_i)^2} \qquad (10)$$

Step 3: The two values *x* and σ are termed as quantizers of BTC. Taking *x* as the threshold value a two-level bit plane is obtained by comparing each pixel value xi with the threshold. A binary block, denoted by B, is also used to represent the pixels. We can use "1" to represent a pixel whose gray level is greater than or equal to *x* and "0" to represent a pixel whose gray level is less than

$$B = \begin{cases} 1 & x_i \geq \bar{x} \\ 0 & x_i < \bar{x} \end{cases} \qquad (11)$$

By this process each block is reduced to a bit plane. For example, a block of 4 x 4 pixels will give a 32 bit compressed data, amounting to 2 bit per pixel (bpp).

Step 4: In the decoder an image block is reconstructed by replacing '1's in the bit plane with H and the '0's with L, which are given by:

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Vol 4, Issue 3, March 2017

$$H = \bar{x} + \sigma\sqrt{\frac{p}{q}} \qquad (12)$$

$$L = \bar{x} - \sigma\sqrt{\frac{p}{q}} \qquad (13)$$

Where p and q are the number of 0's and 1's in the compressed bit plane respectively.

Where xi represents the ith pixel value of the image block and n is the total number of pixels in that block.

- **Filtering**

The compressed image is filtered using Modified Decision Based Unsymmetric Trimmed Median filter (MDBUTMF). The filter is applied for the all the three components (Red, Green and Blue). The filtered images for all the three components are finally concatenated.

a) MDBUHTMF:

The Modified Decision Based Unsymmetric Hybrid Trimmed Median Filter (MDBUHTMF) algorithm processes the corrupted images by first detecting the salt-and-pepper noise. The pixel is checked whether it is noisy or noisy free. That is, if the pixel lies between maximum and minimum gray level and pixel value then it is noise free pixel it is left unchanged. If the pixel takes the maximum or minimum gray level or pixel value or intensity values then it is noisy pixel which is processed by MDBUHTMF.

❖ **Algorithm:**

Step 1: Select image from computer memory into current program. Any given digital image is represented as an array size M*N pixels.

Step 2: Apply digital topology concept which will help in selecting the neighbourhood of a pixels in an image.

Step 3: Select the dimension size of an image in order to calculate the values of pixel in a current image which will also help in obtaining end of file.

Step 4: Repeat the following steps until all the pixels of an image is not checked and end of file is not conquered.

Step 5: Collect the pixels from mask of size 3*3 in order to obtain pixels values in a selected mask.

Step 6: Check whether value of centre pixel is 0 which represent pepper noise or 255 which represent salt noise is present or not.

Step 7: If the pixel values 0 or 255 then the pixels are corrupted and then we have two cases:

Case i): If the selected window contains all the elements as 0's and 255's. Then replace with the mean of the element of window.

Case ii): If the selected window contains not all elements as 0's and 255's. Then eliminate pixel values 0's and 255's and find the median value of the remaining pixels.

Step 8: Apply median filter which is the combination of hybrid and relaxed median filter to calculate value of median of remaining pixels which will be used to replace centre corrupted pixel in a mask.

Step 9: Move mask on each pixels of an image in order to remove all salt noise and pepper noise from current image.

Step 10: When all the corrupted pixels are removed we will obtain the filtered image.

- **Decompression**

The inverse process of compression is known as Decompression. Decompression decompresses the compressed image and the decompressed image will be attained at the end

- **Reconstruction**

The original image was reconstructed using Alternating Minimization algorithm. The Alternating minimization algorithm includes techniques such as PSF (point spread function), Fast Fourier Transform (FFT) and convolution of PSF and FFT. The Inverse Fast Fourier Transform (IFFT) is finally used to reconstruct the fingerprint image. This algorithm is used for further enhancement of the output image.

Proposed System Advantages

- The ratio-distortion performance of the proposed scheme is significantly better than that of existing techniques.
- PSNR value will be high.

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Vol 4, Issue 3, March 2017

- Image compression is useful in, reducing the storage and transmission bandwidth requirements of medical images.
- Resolution scalability, which refers to the ability to decode the compressed image data at various resolutions.
- Quality scalability, which refers to the ability to decode the compressed image at various qualities or signal-to-noise ratios (SNR) up to lossless reconstruction.
- It produces robust security to the users.

V. PERFORMANCE MEASUREMENTS

The Image quality assessment parameters such as PSNR and MSE are used for performance measurements. The input image and the enhanced output image are given as the input. MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio) are some of the image quality assessment parameters which are calculated at the concluding stage of the project. This was calculated in order to prove that the algorithm/ techniques used in our project was superior to the existing one. The MSE and PSNR are calculated to evaluate the processed image. Here the peak signal-to-noise ratio (PSNR) and mean square error (MSE) have been used to obtain the qualitative results for comparison.

Mean Square Error:

The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare image compression quality. The lower the value of MSE, the lower the error.The MSE represents the cumulative squared error between the enhanced and the original image and is given by,

$$\mathrm{MSE} = \sum_{i=1}^{x}\sum_{j=1}^{y} \frac{\left(|A_{ij} - B_{ij}|\right)^2}{x * y} \qquad (14)$$

Where x and y are number of rows and columns of a input image.

3.3.2 Peak Signal to Noise Ratio:

The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed or reconstructed image. PSNR represents a measure of the peak error

$$\mathrm{PSNR(dB)} = 10 * \log\left(\frac{R^2}{\mathrm{MSE}}\right) \ (15)$$

R is the maximum fluctuation in the input image data type. For example, if the input image has a double precision floating-point data type, then R is 1. If it has an 8-bit unsigned integer data type, R is 255.

3.3.3 Compression Ratio:

The compression ratio is used to measure the ability of data compression by comparing the size of the image being compressed to the size of the original image. The greater the compression ratio means the better the wavelet function.

$$\mathrm{CR} = \frac{\text{Output file size (bytes)}}{\text{Input file size (bytes)}} \qquad (16)$$

VI.EXPERIMENTAL RESULTS AND PARAMETER ANALYSIS.

Algorithm is implemented on a group of MR DICOM images. The proposed system is efficient and is less error sensitive iterations, less execution time is achieved compared to others.. The experimental results shown in Figure 7& Figure 8 .Hence the proposed system is efficient and is less error sensitive be the best. But for ROI-based compression computational complexity is also one of the important issues to be considered, while addressing real time applications A new and simple algorithm as explained above is used to encode theimage. The ‘compressed image’ is the image which is generated at the decoder side after reconstruction process.

PROPOSED METHOD RESULTS:

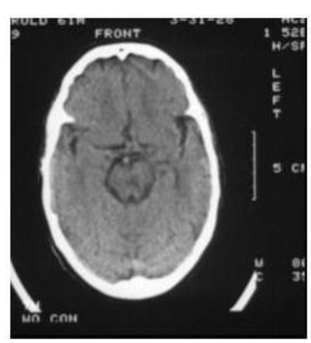

FIG 1: ORIGINAL MAGE

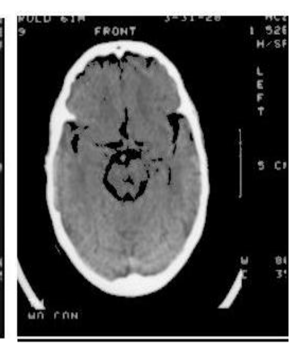

FIG 2: BACKGROUND REMOVED

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Vol 4, Issue 3, March 2017

FIG 3: SELECTING ROI PART IN IMAGE

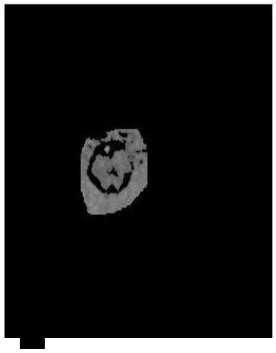

FIG 4: ROI IMAGE

FIG 5: NON ROI IMAGE

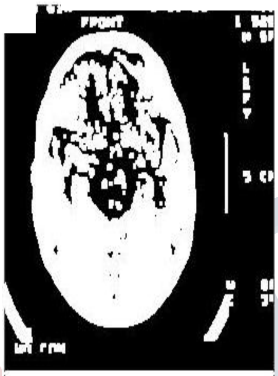

FIG 6: FILTERED IMAGE

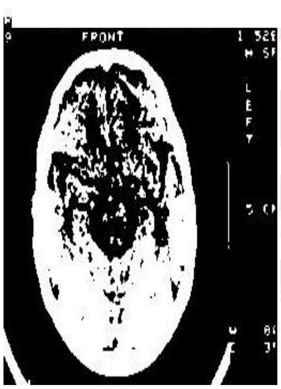

FIG 7: COMPRESSED IMAGE

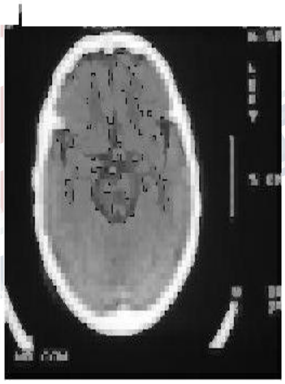

FIG 8: DECOMPRESSED IMAGE

FIG 9: RECONSTRUCTED IMAGE

Comparison between Existing and Proposed System Results:

Parameters	Existing System	Proposed System
MSE	968	0.0636
PSNR	24.3142	60.1301
CR	0.9596	11.8321

VII. CONCLUSION

This project has proposed a novel scheme of compressing the ROI and Non-ROI part of the DICOM Medical Images. The original image is compressed using Haar wavelet transform and Block Truncation Coding (BTC) and then filtered using Unsymmetric Trimmed Median Filter and then decompressed and reconstructed using Alternating Minimization Algorithm. Finally the Performance Parameters are analyzed to evaluate the effectiveness of the proposed approach. This can be used for telemedicine purpose.

ROI-based compression is providing better results as compared with lossless methods, along with preservation of diagnostically important information. Such method is recommended for telemedicine system especially rural area, where network resources have limitations. Advanced version of the proposed method may include the compression based on the information

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Vol 4, Issue 3, March 2017

contents as well as compression based on ROI to be selected automatically.

VIII. FUTURE SCOPE

For telemedicine applications the large amount of bandwidth is required for transmission and storage for processing the medical images. The compression techniques should provide the safe transmission and storage of medical image with limited bandwidth and requirements. To minimize the information loss in medical images a hybrid techniques can be introduced which improves the compression ratio and reduces the information loss. The advanced version for image compression based on information content as well as ROI using textural properties can be introduced as future work for this project

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