Different Wavelets For Medical Image Compression In Telemedicine’s

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Abstract: Transferring medical images from one center to another is common use in telemedicine. These high-quality images stored in DICOM format require higher bandwidth in transmission and large storage space in PACS (Picture Archieving and Communication System) memory. Therefore reducing the image size for preserving diagnostic information has become a need. In this sense, medical image compression is technique that overcomes both transmission and storage cost by lossy and lossless compression algorithms. There are numerous compression methods developed for region-based studies generally used in radiography, computed tomography (CT) and magnetic resonance images (MRI).

The use of digital medical images is increases very fast. Medical images like CT scan, ultrasound, dental X-ray etc, require large amounts of memory storage. Even to transmit an image over a wireless or LAN network could take more time. Due to this reason medical image compression is important. Related to medical images many compression methods are available. However, the lossless (for diagnostic and legal reasons) techniques, which allows for perfect reconstruction of original image, yield compression rates of at most 2 only, while the techniques that yields higher compression rates are lossy. To meet this challenge, we have developed a hybrid compression schemes which is diagnostically lossless with good compression ratio. Due to its simplicity the hardware realization is also easy and not cost effective compare to JPEG method.

Along with that, very limited researchers take a challenge to apply hardware on their implementation. Referring to the previous work reviewed, most of the compression method used lossless rather than lossy. For implementation using software, MATLAB is the famous candidates among researchers. In term of analysis, most of the previous works conducted objective test compared with subjective test. This paper thoroughly reviews the recent advances in medical image compression mainly in terms of types of compression, software and hardware implementations and performance evaluation. Furthermore, challenges and open research issues are discussed in order to provide perspectives for future potential research. In conclusion, the overall picture of the image processing landscape, where several researchers more focused on software implementation and various combination of software implementation.

Keywords:- Matlab, MSE(mean square error);PSNR(peak signal to noise ratio);COC(correlation coefficient);Huffman coding ;CT scan images; Ultrasound images; Dental X- ray.

Introduction: Imaging technology in medicine made for the doctors to see the interior portion of the body. (J. satheeshkumar et al., 2011) for easy diagnosis. It also helped doctors to make keyhole surgeries for reducing the interior parts without really opening too much of the body. Magnetic Resonance Imaging took over X-ray imaging by making the doctors to look at the body’s elusive third dimension. With the CT scanner, body’s interior can be bared with ease and the diseased areas can be identified without causing either discomfort or pain to the patient. Advance medical technology MRI (P.V. Peck, 1988) picks up signals from the body’s magnetic particles spinning to its magnetic tune and with the help of its powerful computer, converts scanner data into revealing pictures of internal organs. Image processing techniques developed for analyasing remote sensing data may be modified to analyse the outputs of medical imaging systems to set best advantage to analyse symptoms of the patient with ease. According to the New England Journal of Medicine, medical imaging is one of the top developments that “changed the face of clinical medicines” during the last millennium. Medical imaging techniques produce very large amounts of data from CT, MRI and PET (cherry, 2001) modalities. As a result large storage space and network bandwidth requirements arise when large amount of medical images are to be stored or transmitted (R Gonzalez et al., 2008) is very important. Many current compression schemes provide a very high compression rate but considerable loss of quality and expensive hardware. However, the cost of using compression must be taken into account, complex compression schemes are more costly to develop, implement, and deploy. A hybrid- coding scheme seems to be the only solution to this twofold problem.

The general theme is to preserve quality in diagnostically critical region. These have provided an impetus to the development of other applications, in particular telemedicine and teleradiology. In these fields, medical image compression is important since both efficient storage and transmission of data through high-bandwidth digital communication lines are of crucial importance.

A close examination of the algorithms used in real-time medical image processing applications has revealed that many fundamental actions had involved matrix or vector operations. Most of these operations are matrix transforms that include fast Fourier transform (FFT), discrete wavelet transforms (DWT), and other recently developed transforms such as finite Radon, as well as curvelet and ridgelet transforms which are used in either two-dimensional (2-D) or three-dimensional (3- D) medical imaging. Unfortunately, computational complexity for the matrix transform algorithms is in the order of O (N × log N) for FFT to O (N2 × J) for the curvelet transform (where N is the transform size and J is the maximum transform resolution level) which are computationally intensive for large size problems. Thus, efficient implementations for these operations are of interest not only because matrix transforms are important in their own right, but also because they automatically lead to efficient solutions to deal with massive medical volumes.

1 Compression

With the increasing use of Computed Tomography (CT), and Magnetic Resonance Imaging (MRI), the use of computers in facilitating their processing and analysis has become necessary. Medical Images incorporates information about the human body which is utilized for various purposes such as surgical and analytic plans. Medical image compression is used in applications such as summing up patient's information and IoT applications [4,18,19]. Concerning the significance of medical image information, lossless compression is preferred. Image compression may be lossy or lossless. Lossless compression is desired for storage purposes and often for medical imaging, specialized drawings, clip art, or comics. Lossless compression algorithms are the original data perfectly recreated from compressed data. In a lossy compression, only the approximation of the original data is reconstructed.

2 Wavelet Transform

Fourier transforms only gives what frequency component exists in a signal. Fourier transforms cannot tell what time; the frequency components occur. However, the time-frequency component is needed in most cases. The representation of a function of a wavelet transform is called the daughter wavelets. These daughter wavelets are scaled and interpreted duplicates of the central oscillating waveform called the mother wavelet. The wavelet changes are more beneficial over the old Fourier transform. The wavelet transform describes the functions that have disconnection and sharp points, and for precisely deconstructing and recreating finite, non-periodic, additionally non-stationary signals along with periodic or stationary signals. The wavelet transforms can be categorized into two types such as Discrete Wavelet Transform (DWT) and a Continuous Wavelet Transform (CWT). Both of these wavelets transform to give the time and frequency of the signal and are called analog transforms. CWTs function on each scale and interpretation conceivable, through the DWTs utilizes an exact subset of scale and interpretation esteems.

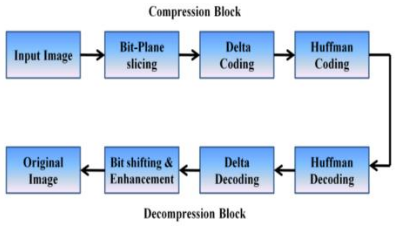
3 Wavelet Transform in Image Compression

Wavelet Transform utilizes both the spatial and frequency correlation of data by dilations (or contractions) and translations of mother wavelet on the input data. Wavelet Transform supports the multi-resolution analysis of data. It can be convenient to different levels according to the details required, which permits reformist transmission and zooming of the image without the requirement for additional capacity. Another hopeful element of wavelet change is its symmetric nature that is both the forward and the inverse transform has the similar intricacy, constructing fast compression and decompression routines. Wavelet transform qualities are appropriate for image compression including the capacity to assess Human Visual System's (HVS) attributes awesome energy compaction capabilities, vigor under the transmission, high compression ratio, etc. In the sub band coding plan, the signal is disintegrated using filter banks. The usage of the wavelet compression scheme is much related to that of sub band coding plan. The output of the filter banks is encoded, down sampled, and quantized. The decoder interprets the coded representation, up-samples, and recomposes the signal. The proposed a new filter designed based on a 9/7 wavelet lifting scheme. There are some advantages when compared to 5/3 wavelet filter relaxation in the design constraints that are implementing integer arithmetic without division it improves our compression performance. It gives better performance when compared to JPEG 2000 using a 5/3 wavelet lifting scheme [2].

Related Work

Block diagram:-

Figure 1 proposed methods block diagram:-



Our approach for Medical Image compression is based on the basic coding techniques like Huffman coding and Delta coding. Based on the previous study we come to know that in medical field plenty of images are involved and processing of those images with high efficiency and in time is important. As we know JPEG gives high compression but due to its DCT (Discrete Cosine Transform) block the complexity of the hardware increases compare to the simple compression technique as shown in Figure.

Even probability of losing important data of medical image is more in JPEG method. So a algorithm is proposed which contain the combination of basic techniques like Huffman coding, Predictive Delta coding, Bit plane slicing which provide sufficient CR (compression ratio) with better MSE, PSNR and COC results. 3.1 Proposed algorithm steps Step: 1 According to the algorithm first we apply the Bit plane slicing technique to reduce the redundant data and eliminating the lower bit –plane from it. In image higher bit plane contain the more informative data rather than lower level so if we neglect the lower plan we will not loss more information in case of this medical image as you can see the result in figure.

Basics of wavelet transform

The wave is an infinite length continuous function in time. In contrast, wavelets are localized waves. A wavelet is a waveform of an effectively limited duration that has an average value of zero. Wavelet transform of a function is the improved version of Fourier transform. It provides the time-frequency representation. . The fundamental idea of wavelet transforms is that the transformation should allow only changes in time extension, but not shape. This is affected by choosing suitable basis functions that allow for this changes in the time extension are expected to be conform to the corresponding analysis frequency of the basis function. Wavelet transforms are based on small wavelets with limited duration.

The Continuous Wavelet Transform or CWT formally it is written as:

$$\gamma(s,r)=\int f(t)\ \psi^{*}s,r\ (t)dt \qquad (1)$$

Where * denotes complex conjugation. This equation shows how a function f (t) is decomposed into a set of basics functions ψs,-(t), called the wavelets. The variables s and - are the new dimensions, scale and translation, after the wavelet transform equation (2) gives the inverse wavelet transform

$$f(t)=\iint \gamma(s,r)\psi s,r(t)drds \qquad (2)$$

The wavelets are generated from a single basic wavelet ψ(t), the so-called mother wavelet, by scaling and translation:

$$\Psi s,\ r(t)=1/\sqrt{s}\ \psi(t\text{-}r/s) \qquad (3)$$

In (3) s is the scale factor, - is the translation factor and the factor s-1/2 is for energy normalization across the different scales.

Discrete wavelet transform

Discrete wavelets are not continuously scalable and translatable but can only be scaled and translated in discrete steps. This is achieved by modifying the wavelet representation (3) to create

$$\Psi j,\ k(t)=1/\sqrt{s0\ j}\psi(t\text{-}kr0s0/s0\ j\ ) \qquad (4)$$

Although it is called a discrete wavelet, it normally is a (piecewise) continuous function. In (10) j and k are integers and s0 > 1 is a fixed dilation step. The translation factor -0 depends on the dilation step. The effect of discretizing the wavelet is that the time-scale space is now sampled at discrete intervals. We usually choose s0 = 2 so that the sampling of the frequency axis corresponds to dyadic sampling. This is a very natural choice for computers, the human ear and music for instance. For the translation factor we usually choose -0 = 1 so that we also have dyadic sampling of the time axis. In the analysis of both numerical and functional methodologies, a Discrete Wavelet Transform (DWT) can be used. DWT is a kind of wavelet transform for which the wavelet functions are discretely sampled by the other wavelet transforms. A major advantage of discrete wavelet transform over the Fourier transform is the effect of temporal resolution.

Another method of decomposing signals that has gained a great deal of popularity in recent years is the use of wavelets. Decomposing a signal in terms of its frequency content using sinusoids results in a very fine resolution in the frequency domain, down to the individual frequencies. However, a sinusoid theoretically lasts forever; therefore, individual frequency components give no temporal resolution. In other words, the time resolution of the Fourier series representation is not very good. In a wavelet representation, we represent our signal in terms of functions that are localized both in time and frequency [3]. Recently, wavelets have become very popular in image processing, specifically in coding applications for several reasons [4]. First, wavelets are efficient in representing non-stationary signals because of the adaptive time frequency window. Second, they have high décor relation and energy compaction efficiency. Third, blocking artifacts and mosquito noise are reduced in a wavelet based image coder. Finally, the wavelet basis functions match the human visual system characteristics, resulting in a superior image representation. Compared with DCT, DWT uses more optimal set of functions to represent sharp edges than cosines. Wavelets are finite in extent as opposed to sinusoidal functions. Here, the whole image is first transformed by wavelet transform, then the actual encoding is applied on the complete wavelet coefficients, as shown in the Figure 1.Although these methods effectively overcome the blocking artifact problem, it is not possible to encode the image during the transform stage.

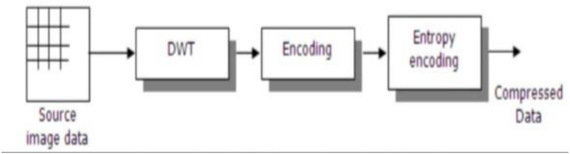


Figure 2 The typical DWT based Image coding

The fundamental idea behind wavelets is to analyze the signal at different scales or resolutions, which is called multi resolution. Wavelets are a class of functions used to localize a given signal in both space and scaling domains. A family of wavelets can be constructed from a mother wavelet. Compared to Windowed Fourier analysis, a mother wavelet is stretched or compressed to change the size of the window. In this way, big wavelets give an approximate image of the signal, while smaller and smaller wavelets zoom in on details. Therefore, wavelets automatically adapt to both the high-frequency and the low frequency components of a signal by different sizes of windows. Any small change in the wavelet representation produces a correspondingly small change in the original signal, which means local mistakes will not influence the entire transform. The wavelet transform is suited for non-stationary signals, such as very brief signals and signals with interesting components at different scales.

Discrete cosine transform:-

The Discrete Cosine Transform (DCT) algorithm is well known and commonly used for image compression. DCT converts the pixels in an image, into sets of spatial frequencies. It has been chosen because it is the best approximation of the Karhunen loeve transform that provides the best compression ratio [5]. The DCT work by separating images into the parts of different frequencies. During a step called Quantization, where parts of compression actually occur, the less important frequencies are discarded, hence the use of the lossy. Then the most important frequencies that remain are used retrieve the image in decomposition process. As a result, reconstructed image is distorted. Compared to other input dependent transforms, DCT has many advantages [6]:

1. It has been implemented in single integrated circuit.

2. It has the ability to pack most information in fewest coefficients.

3. It minimizes the block like appearance called blocking artifact that results when boundaries between sub-images become visible.

The DCT can be extended to the transformation of 2D signals or images. This can be achieved in two steps: by computing the 1D DCT of each of the individual rows of the two-dimensional image and then computing the 1D DCT of each column of the image. If represents a 2D image of size x(n1 , n2) N × N , then the 2D DCT of an image is given by:

$$Y[j,k] = C[j]C[k]\sum_{m=0}^{N-1}\sum_{n=0}^{N-1} x[m,n]\cos\left(\frac{(2m+1)j\pi}{2N}\right)\cos\left(\frac{(2n+1)k\pi}{2N}\right) \quad \ldots\ldots eq$$

Where j, k, m, n = 0, 1, 2..., N − 1 and

$$C[j] \ \ and \ \ C[k] = \begin{bmatrix} \sqrt{\frac{1}{N}} & \text{for } j,k = 0 \\ \sqrt{\frac{1}{N}} & \text{for } j,k = 1,2,\ldots,N-1 \end{bmatrix}$$

Similarly the 2D IDCT can be defined as

$$x[m,n] = \sum_{j=0}^{N-1}\sum_{k=0}^{N-1} C[j]C[k]Y[j,k]\cos\left(\frac{(2m+1)j\pi}{2N}\right)\cos\left(\frac{(2n+1)k\pi}{2N}\right) \quad \ldots eq.$$

The DCT is a real valued transform and is closely related to the DFT. In particular, a N × N DCT of x(n1,n2) can be expressed in terms of DFT of its even-symmetric extension, which leads to a fast computational algorithm. Because of the even-symmetric extension process, no artificial discontinuities are introduced at the block boundaries. Additionally the computation of the DCT requires only real arithmetic. Because of the above properties the DCT is popular and widely used for data compression operation.

In the DCT compression algorithm,

- The input image is divided into 8-by-8 or 16-by-16 blocks
- The two-dimensional DCT is computed for each block.
- The DCT coefficients are then quantized, coded, and transmitted.
- The receiver (or file reader) decodes the quantized DCT coefficients, computes the inverse two-dimensional DCT.
- (IDCT) of each block. Puts the blocks back together into a single image.

Different types of wavelets are given below these all types of wavelets are used for image compression for telemedicine application

1. Haar wavelet	2. BNC wavelet
3. Coiflet wavelet	4. Daubechies wavelet
5. Bionomial wavelet	6. Mathieu wavelet
7. Legendre wavelet	8. Beta wavelet
9. Hermitian wavelet	10. Hermitian Hat wavelet
11. Meyer wavelet	12. Maxican Hat wavelet
13. Shannon wavelet	

Figure flow chart

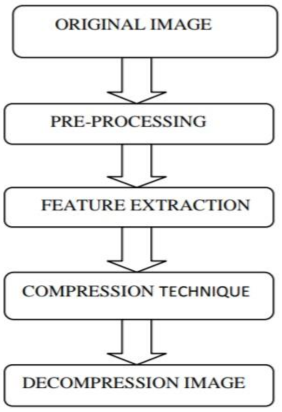


Figure:- Flow diagram of The proposed method

Steps involved in the process:

Step 1: Consideration of Original Image

Initially the input image is fed to the system, the input image may be a highly non stationary one, hence we convert the size of the input image to 256 x 256. In gray scale coding even if the input image is a color image it will be converted into gray scale image using RGB converter.

Step 2:Pre-Processing

After the input image is taken, in the Pre-processing step each and every neighborhood pixel of an input image should have a new brightness value corresponding to the output image. Such pre-processing operations are also known as filtration. Types are enhancement (image enhancement for shape detection), image restoration (aim to stem degradation using knowledge about its nature of an image; i.e. relative motion of camera image and object, wrong lens focus etc.), image compression

Step 3: Feature Extraction

In the extraction process the input image data is segmented and then the input data will be transformed into a reduced represented set of features. It is useful on a selection of situations Where it helps to stem data information that is not important to the specific image processing task (i.e. background elimination).Transforming the input data into a particular set of features is called as feature extraction.

Step 4: Compression technique

Basically, there are two types of image compression techniques used with digital image and video, lossy and lossless. Lossy compression methods include DCT (Discrete Cosine Transform), Vector Quantization and Huffman coding. Lossless compression method include RLE scheme (Run Length Encoding), string-table compression and LZW (Lempel Ziv Welch). Here we will use wavelet transform for compress the medical image.

Step 5: Decompressed Image

In the decompression process, the original image is extract.

Parameters for Quantification of image Results

1 MSE (Mean Square Error)

Let X is a random variable and c is a number. Denote by ε the difference:

$$\varepsilon = X - c$$

Where ε is a random variable. There are two circumstances where ε may be regarded as an error. c is the unknown value of a parameter of a distribution, and X is an estimator of this parameter. In this context, it is usual to denote the estimator by θ^* (instead of X), and the value of the parameter by $\theta 0$ (instead of c). ε is called the "estimation error" of θ^* . A good estimator is close to $\theta 0$ on the average. Just how close is usually measured by the mean of the squared estimation error ε. This quantity is called the Mean Square Error (MSE) of the estimator θ^*:

$$MSE = E[(\theta^* - \theta 0)^2]$$

The MSE is equal to the sum of the variance and the squared bias of the estimator

$$MSE = Var(\theta^*) + Bias(\theta^*)^2$$

The MSE thus assesses the quality of an estimator in terms of its variation and unbiasedness. Note that the MSE is not equivalent to the expected value of the absolute error. Since MSE is an expectation, it is not a random variable. It may be a function of the unknown parameter θ, but it does not depend on any random quantities. However, when MSE is computed for a particular estimator of θ the true value of which is not known, it will be subject to estimation error. In a Bayesian sense, this means that there are cases in which it may be treated as a random variable. (R. Gonzalez et al., 2008)

2 PSNR (peak signal-to-noise ratio)

The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codecs. The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codes it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR.A higher PSNR would normally indicate that the reconstruction is of higher quality. One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec and same content. It is most easily defined via the mean squared error (MSE) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j)-K(i,j)]^2$$

The PSNR define as:

$$PSNR = 10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$PSNR = 20.\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

Here, MAXI is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAXI is 2 B −1. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space. Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, where higher is better. Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB. When the two images are identical, the MSE will be zero. For this value the PSNR is undefined. (R. Gonzalez, 2008.

3 Correlation Coefficient (COC)

The maximum positive correlation is 1.00. Since the correlation is the average product of the standard scores for the cases on two variables, and since the standard deviation of standardized data is 1.00, then if the two standardized variables co-vary positively and perfectly, the average of their products across the cases will equal 1.00.On the other hand, if two things vary oppositely and perfectly, then the correlation will equal 1.00.We therefore have a measure which tells us at a glance whether two things co vary perfectly, or near perfectly, and whether positively or negatively. If the coefficient is, say, .80 or .90, we know that the corresponding variables closely vary together in the same direction; if -.80 or -.90, they vary together in opposite directions. Zero or near zero correlation means simply that two things vary separately. That is, when the magnitudes of one thing are high; the other's magnitudes are sometimes high, and sometimes low. It is through such uncorrelated variation--such independence of things which we can sharply discriminate between phenomena of correlation coefficient between two variables is defined as the covariance of the two variables divided by the product of their standard deviations: (R. Gonzalez, 2008).

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X\sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X\sigma_Y}$$

Result:-

1. CT scan Images analyses

From figure below we can see that we are getting good result of MSE (Mean Square Error), PSNR (Peak Signal to Noise Ratio) and COC (correlation coefficient) in comparison to the popular JPEG method for our proposed method.

Figure- MSE results for abdominal CT scan

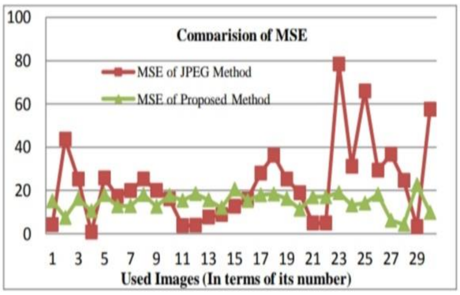


Figure -PSNR results for abdominal CT scan

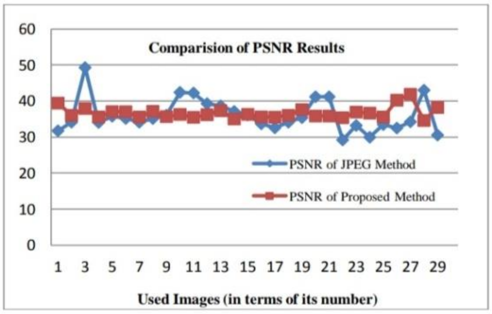


Figure COC results of abdominal CT scan

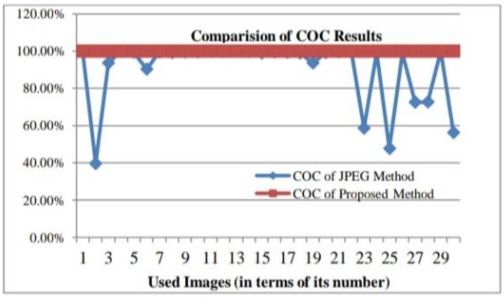
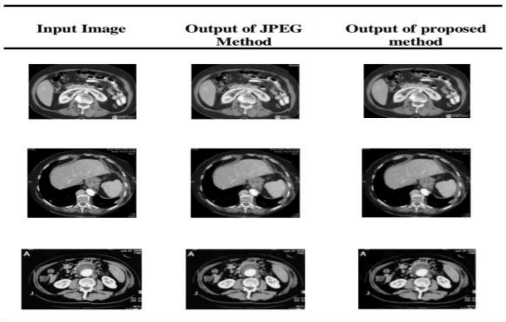


Figure Input-Output comparison for two different methods



2. Ultrasound Images analyses

From figures below we can see that we are getting good result of MSE (Mean Square Error), PSNR (Peak Signal to Noise Ratio) and COC (correlation coefficient) in comparison to the popular JPEG method for our proposed method.

Figure MSE results for Ultrasound Images

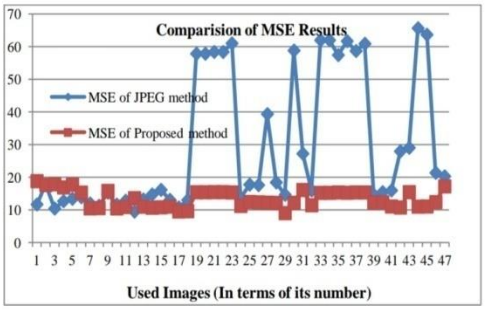


Figure PSNR results for Ultrasound images

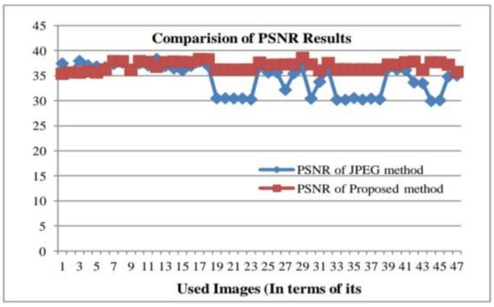


Figure COC results for Ultrasound images

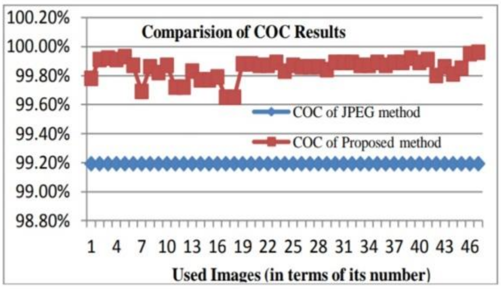
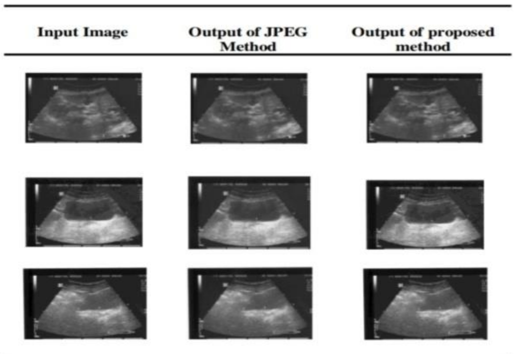


Figure-Input-Output comparison for two different methods



Conclusion:

Compressing the whole image with lossy algorithm results with losing diagnostic information on critical areas. On the other hand, compressing completely with a lossless algorithm does not provide a remarkable compression ratio and memory space. Therefore, region-based compression has become a research area to investigate for higher compression rates and acceptable other objective criteria parameters. For this purpose, the image is generally segmented into regions, ROI and Non-ROI. ROI part involves the most significant diagnostic data and the Non-ROI part contains non-critical information by a specialist. By segmenting these regions lossless algorithm is applied to the ROI(s) and lossy algorithm to the Non-ROI parts. In this way, it is possible to obtain higher performance results while maintaining significant diagnostic data. It is important to choose compression technique and the related parameters appropriately for the purpose of the study. Thus, diagnostic information can be preserved, and loss of detail can be acceptable for radiologists. Consequently, compressed images will save data by occupying less memory by preserving the diagnostic information. In this way, the transmission of images from one center to another can be done more quickly with lower bandwidth for the telemedicine applications. Besides, compressed medical images contribute to the database management of PACS by having less memory.

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