HYBRID IMAGE COMPRESSION OF MEDICAL IMAGES

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Abstract- Digital medical image which produces digital pictures of human body provides powerful tools for diagnosis, treatment and surgery. Hence becomes a major aspect of modern healthcare delivery. It is a fast growing area with the richest source of information and variety of modalities such as X-ray transmission imaging (X-ray), magnetic resonance imaging (MRI), computed tomography (CT), ultrasound images, positron emission tomography (PET) and many others. There exists a need for compression of these images for storage and communication purposes. Therefore, in this paper we propose a new compression algorithm which comprises the Block based PCA and Haar Wavelet algorithm (DWT family). At first, we apply the block based PCA on ROI region (diagnostically important area) followed by the Haar wavelet transform on NROI (diagnostically unimportant area) region. Here, Block based PCA is used for lossless compression of medical image whereas Haar Wavelet is utilized for lossy image compression. In this paper we are applying the above proposed technique on samples of five different CT images. The results are calculated using parameters like PSNR (image quality), CR (Compression Ratio), MSE (Mean Square Error), SSIM (Structure Similarity Index) and BER (Bit Error Rate).

Index Term:- ROI; NROI; PSNR; CR; MSE; SSIM; BER; Block Based PCA and Haar Wavelet.

I.INTRODUCTION

All the digital images are usually a 2-D array of pixels. Pixels are fundamental picture elements from which these digital images are made. Typically, pixels are stored in an arranged rectangular cluster. The extent of a picture is controlled by the measurements of this pixel exhibit. Each pixel has its own intensity value and brightness. If each pixel will have the same amount of intensity then the whole image will be uniformly colored figure. Color pictures; also have intensities from the darkest and lightest of three unique hues, Red, Green and Blue. Along these lines, two fundamental kinds of computerized pictures, B&W and Color, are known as gray-scale and RGB pictures.

Image compression plays a vital role in applications like video conferencing, remote sensing, medical imaging, magnetic resonance imaging etc. In most images the neighboring pixels are correlated and hold redundant information. The task then is to find out less correlated representation of the image. Two elementary components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source image. Irrelevancy reduction omits parts of the signal that is not noticed by the signal receiver. Number of bits required to represent the information in an image can be minimized by removing the redundancy present in it. [7]

Digital Information Systems, Hospital Information Systems (HIS), and its special case like the Radiology Information Systems (RIS) and Picture Archiving & Communication Systems (PACS) forms the information infrastructure of the modern health care. It is a collective standard of medical information systems and information technology, where the computers store and forward medical information for long distances health care, for e.g., Remote Telesurgery. In Telesurgery, the surgeons carry out minimally invasive operations with more control using robotic tools, as shown in Fig. 1. In Remote Telesurgery, the surgeons and patient are separated by miles of distances, as shown in Fig.2. [8].

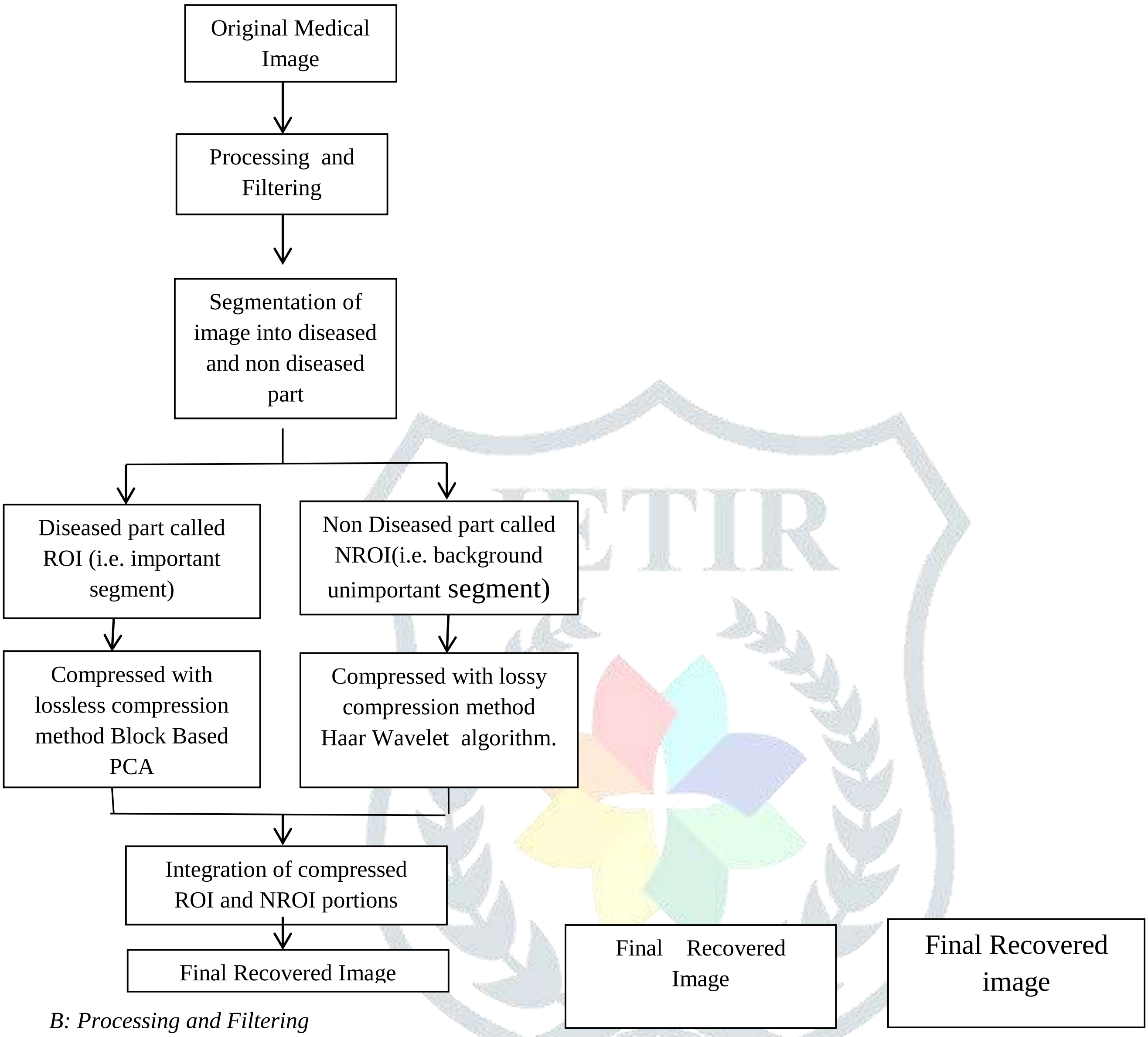
Fig 1: Tele surgery [8]

Fig 2: Remote Tele surgery with Remote Control Arms [8]

So, in Hospital Information System the major challenges existing are the management of disk space i.e storage space for the processed medical images as well as the transmission time and bandwidth required for their transmission.

II: METHODOLOGY

A: Flow Chart



B: Processing and Filtering

Preprocessing is divided into two stages:

Gray- Scale Image: When we convert any Image weather a colored one or non-colored into Black and white (b&w) then this process is referred as gray-scaling. Matlab stores a gray scale image in the form of a square matrix which indicates the values of pixels of which the image is made of. Converting an image to be processed into a gray-scale image have many advantages during the processing like ease of processing is there. Many applications which could not perform in color image can easily perform in gray-scale images. Also the information content of the image can be highlighted easily in gray-scale as compared with colored one.

Image Enhancement: After gray-scaling we are doing enhancement of the poor pixels of the host medical image. As the name suggest image enhancement enhances the quality of picture such that the information content of the image can clearly and easily studied. At the same time it reduces the chance of mistakes by making things more clear. Many algorithms are available for this purpose. Here we have used histogram equalization for the same.

C: Segmentation

Selecting a portion or a particular part of an image is called its segmentation. Segmentation is done in order to recognize ROI (Region of Interest) i.e. diagnostically important area. Segmentation is very important part of compression method as without it ROI can never detect.
Extracting and studying the ROI portion of the host medical image is the key point of medical image compression.

Segmentations can be done in many available ways like automatic or manual detection. Usually in the case of medical images segmentations are preferred to be done manually so as to avoid any kind of negligence in important data.

While in other fields related with image compression segmentations are preferred automatically for the accuracy purpose. Via segmentation we can extract more than one ROI from the same image. The stage of segmentation should be very accurate because it will directly affect the results of simulations.

Usually, segmentation methods can be divided into two main categories: region-based and edge-based methods. In this work, we use an edge-based algorithm.

The **contour** search is carried out using a threshold operator which assigns the value $I+$ to the pixel with the intensity greater than a fixed threshold, and $I-$ to the pixel with the intensity less than the threshold

If $Ix,\geq$ threshold => $I'x,=I+$

If $Ix,<$ threshold => $I'x,y=I-$

where, Ix,y is the intensity for the pixel with coordinates (x, y).

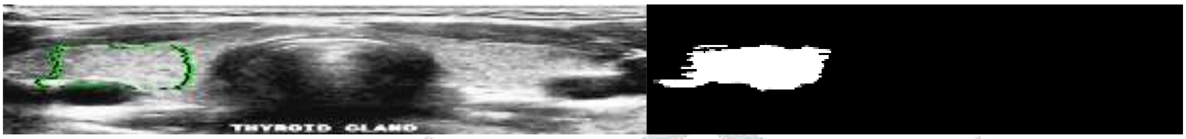


Fig:3: Segmentation Of thyroid gland upto 100 iterations

D: The General PCA algorithm

Principal component analysis works by transforming a set of correlated data into another set of uncorrelated data. The description of PCA algorithm on compression of image has been made broadly in and but however few variances have been found out within the papers. Since solely grey-scaled image is concerned in our work, the input image $g\ (x,\ y)$ or Z is of associate degree M×N monochrome picture where by every element signify the intensity value.

$$Z = g(x,y) = \begin{bmatrix} g(0,0) & \cdots & g(0,N-1) \\ \vdots & \ddots & \vdots \\ g(M-1,0) & \cdots & g(M-1,N-1) \end{bmatrix}$$

PCA is begun by subtracting each element with the mean obtained along the row. As a consequence, all elements are going to be redressed by the expedient of the mean on the row, leading to row element adjust, $(x,\ y)$or Z. Whereas Covariance is applied on the mean-adjusted matrix, Z to measure the linear relationships between each variables. The corresponding matrix is a square matrix (N×N) and the eigenvectors and eigen values for the matrix is calculated.

$$Cov = \begin{bmatrix} cov(Z_1,Z_1) & \cdots & cov(Z_1,Z_k) \\ \vdots & \ddots & \vdots \\ cov(Z_k,Z_1) & \cdots & cov(Z_k,Z_k) \end{bmatrix}$$

The diagonal elements Cov(i,j) represent the variances for the columns of Z. The off-diagonal Cov(i,j) represent the covariance's of columns i and j. Its turns out that the eigenvector with the highest eigen value is principal components (k) of the image. Once the number of principal components is determined, a feature matrix, FV containing all the corresponding eigenvectors will be formed,

$$Feature\ Vector = FV = [\lambda_1, \lambda_2, \ldots, \lambda_k](N \times k)$$

The transpose of the feature matrix will be multiplied with the transposed of the mean adjusted matrix to obtain the compresses data with reduced dimensionality,

$$Final\ data = FD = \left[FV^T \times \overline{g(x,y)}^T\right](k \times M)$$

To recover back the original picture, with or with no whole set of eigenvectors,

$$PCA\_Image = (FV * FD)T + mean$$

E: Block-by-block PCA

The main idea is rather than compressing the whole image at once, we tend to have an interest in acting on the sub - block of the original picture. The input image is partitioned-off into blocks of dimension n and PCA algorithm was implemented one-by-one on every blocks. Each block $Zith$ consists of intensity values $(x,\ y)$ where ith signify the block number of the image.

$$Z_{ith} = \begin{bmatrix} g(0,0) & \cdots & g(0,n-1) \\ \vdots & \ddots & \vdots \\ g(n-1,0) & \cdots & g(n-1,n-1) \end{bmatrix}(\mathrm{n{\times}n})$$

In this work, compression ratio is developed based on the matrix size stored in the compressed data:

$$CR_B = 1 - \left(\frac{nk}{MN} \times \frac{MN}{n^2}\right)$$

Where $\frac{MN}{n^2}$ is the total number of blocks for an image with size M×N.

F: Discrete Wavelet Transform (DWT)

Under this whole image data is presented as a set of high pass and low pass coefficients. The image is then passed through filter which decomposes it into its detailed approximation coefficients. Then these coefficients are separated as LL, HL, LH, and HH coefficients. Finally all the coefficients are discarded except LL. Then it is pass through second level. After that LL is subjected to second level to finally have the desired compression percentage.

HAAR Wavelet Transform

HAAR wavelet is one of the family member of DWT. Haar wavelet compression is an efficient way to perform both lossless and lossy image compression. It relies on averaging and differencing values in an image matrix to produce a matrix which is sparse or nearly sparse. A sparse matrix is a matrix in which a large portion of its entries are 0. A sparse matrix can be stored in an efficient manner, leading to smaller file sizes. In these notes we will concentrate on grayscale images; however, rgb images can be handled by compressing each of the color layers separately. The basic method is to start with an image A, which can be regarded as an m × n matrix with values 0 to 255. In Matlab, this would be a matrix with unsigned 8-bit integer values. We then subdivide this image into 8 × 8 blocks, padding as necessary. It is these 8 × 8 blocks that we work with.

In the proposed methodology the separated NROI part is compressed with the help of the Haar wavelet transform and then reconstructed at the receiver end.

G: Performance Parameters

In any medical images the following performance parameters are used (a) BER (b) PSNR, (c) CR, (d) SSIM and (e) MSE.

(a)Mean Squared Error

In statistics, the mean squared error or MSE of an estimator is a technique to compute the amount by which an estimator diverges from the original value of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root mean square error or RMSE, which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard error.

$$MSE = \frac{1}{MN}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\|I(i,j) - K(i,j)\|$$

(b) Peak Signal to Noise Ratio

The phrase peak signal-to-noise ratio i.e. PSNR, is a technical term used for the ratio between the maximum possible power of a input signal to the power of noise that disturb the fidelity of its illustration. This is most easily defined through the mean squared error (MSE) as follows:

$$MSE = \frac{1}{MN}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\|I(i,j) - K(i,j)\|$$

The PSNR is expressed as:

$$PSNR = 10\log_{10}\left(\frac{{MAX_1}^2}{MSE}\right)$$

Here, *MAX1* shows the maximum desirable pixel value of the image.

(c)Data Compression Ratio

It also known as compression power, is a computer-science term used to quantify the reduction in data- representation size produced by a data compression algorithm.

$$\text{Compression Ratio} = \frac{\text{Uncompressed Size}}{\text{Compressed Size}}$$

Sometimes the space savings is given instead, which is defined as the reduction in size relative to the uncompressed size:

$$\text{Space Saving} = \left[1 - \frac{\text{Compressed Size}}{\text{Uncompressed Size}}\right]$$

(d)Structural Similarity (SSIM) Index

The Structural similarity (SSIM) index is a technique for calculating the similarity between two different images. The SSIM parameter is a full reference metric i.e. the measuring of digital image quality on the basis of an initial uncompressed or noise-free image as reference. SSIM is designed to enhance on conventional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human eye perception.

The SSIM parameter is calculated on various windows of an image. The measure between two windows and of common size N×N is:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu^2{}_x + \mu^2{}_y + c_1)(\sigma^2{}_x + \sigma^2{}_y + c_2)}$$

(e)Bit Error Rate (BER)

Bit error rate is basically a percentage of the bits per errors divided by the total no.of bits transmitted or received.

$$BER = \frac{\text{Error Bit}}{\text{Total no. of transmitted}}$$

III: RESULTS AND DISCUSSIONS

(a)Simulation results (Single ROI)

Under this section the medical image is partitioned into two separate regions namely diagnostically important part called Region of Interest (ROI) as well as Background region i.e. diagnostically unimportant region called Non Region of Interest (NROI).

Table 5.1 shows the ROI and NROI portions of thyroid gland as well as brain tumor ,Spine, Lungs cancer and GI Track CT images.

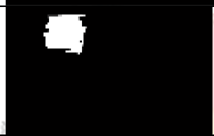
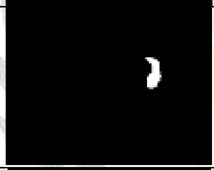
Name	Image	ROI	NROI	Final Recovery
Thyroid Gland				
Brain Tumor				
Spine				
Lungs				
GI Track				

Table 1: ***Performance of Different sampled Images having single ROI***

Table 2 shows the values of simulations. CR which stands for compression ratio gives the ratio of compressed image to the original image. PSNR which stands for Peak Signal to Noise Ratio is measured in db. MSE which stands for Mean Square Error is a measure of error while recovering the original image at the receiver end. SSIM which stands for Structure Similarity Index is a measure of similarities between the transmitted and received image. BER which stands for Bit Error Rate is a measure of no.of error bits while transmitting and receiving ends.

S.no	Recovered Image	CR	PSNR	MSE	SSIM	BER
Thyroid Gland		0.905933	85.8707	12.1272	0.005544	1.5159
Brain Tumor		0.9594	95.54	14.2569	0.00254	2.365
Spine		0.961443	95.2252	4.75885	0.00009	0.594857

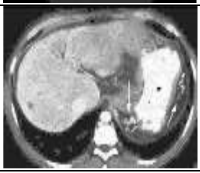
Lungs		0.979018	97.479	0.51406	0.025905	0.064257
GI Track		0.922599	87.8505	9.94901	0.004474	1.2363

Table 2: Performance Evaluation Parameter of above images

(b) Simulation results (double ROI)

Following table 3 is showing the simulation results of ct medical images having double Region of Interests (ROI's).During medical diagnoses there are many situations where there is a need to analyze more than one part of any image. Because there is a possibility of having useful information in that area. Therefore practice of this kind of simulation is very important in medical field.

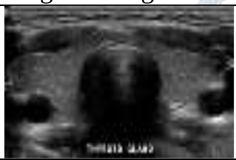
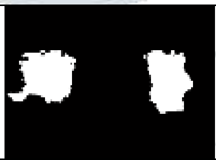
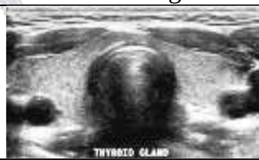
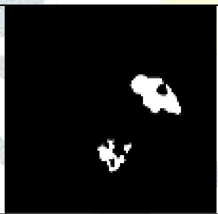
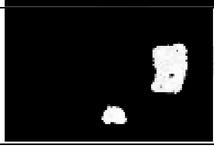
Name	Original Image	Double ROI's	Non-ROI	Recovered Image
Thyroid Gland				
Brain Tumor				
Spine				
Lungs				
GI Track				

Table 3: Performance of Different sampled Images having single ROI

From the above table 4 shown below we can clearly conclude that because of having double ROI's defiantly the quality index of images is gone a little done. But still the PSNR value is maintained at least above 75 dB in every case.

Name	Recovered Image	CR	PSNR	MSE	SSIM	BER
Thyroid Gland		0.804811	78.6012	25.0884	0.0117843	3.13605

Brain Tumor		0.949714	91.8011	6.70206	0.00623106	0.837758
Spine		0.796876	78.3809	25.6474	0.00537298	3.20592
Lungs		0.960919	94.7084	5.01126	0.00586033	0.626408
GI Track		0.890003	84.3045	14.1835	0.00572709	1.77293

Table 4: Performance Evaluation Parameter of above images with double ROI's

IV: CONCLUSION

By processing the proposed technique we come to a conclusion that we are able to achieve the aim which was set by us during the survey of the proposed problems.
The Peak Signal to Noise Ratio (PSNR) of the medical images having Double ROI is also above 75dB. Also the compression ratio (CR) is considerably high for the images having double Region of Interest (ROI's).
In medical field the requirement of this kind of work is there. And our work is a supplement in medical field.

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