A Novel Algorithm For Medical Image Compression In Telemedicines

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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 it's simplicity the hardware realization is also easy and not cost effective compare to JPEG method.

Keywords: MSE(mean square error);PSNR(peak signal to noise ratio);COC(correlation coefficient);CR(compensation ratio); Huffman coding ;Delta 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 it's 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 analyase 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 regioThese 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 .

Despite their advantages, most 3-D medical imaging algorithms are computationally intensive with matrix transformation as the most fundamental operation involved in the transform-based methods. Therefore, there is a real need for high-performance systems, whilst keeping architectures flexible to allow for quick upgradeability with real-time applications . Moreover, in order to obtain efficient solutions for large medical data volume, an efficient implementation of these operations is of significant 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 × logN) 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.

Related Work

This work summarizes review of previous works that have done on Medical image compression related topics. Following are different methods and techniques used.

1.Medical image compression using integer multi-wavelet transforms

In the proposed method integer wavelet transform is used in compressing the image. The compressed image is decomposed by the multiwavelet transform. The encoding is done based on maximum value of image pixel, original value is reduced based on the neighboring pixel value. The final image obtained by this process is an encoded bit stream image which is in binary image (i.e 0‟s and 1‟s). Receiver decodes the incoming bit stream value, decompress it and reconstructs the original image. Major advantage of this method is that the mean square error is reduced when compared to other transforms and the compression ratio is significantly increased.

The original image is taken as a test images input image of size is 256 x 256.

2.ROI based DIACOM images technique in telemedicine Many classes of images contain spatial regions which are more important than other regions. For medical images, only a small portion of the image might be diagnostically useful, but the cost of a wrong interpretation is high. Hence, Region Based Coding (RBC) technique is significant for medical image compression and transmission. A CT or MRI image contains three parts, ROI (the diagnostically important part), Non-ROI image part, and the background (part other than image contents) .The ROI is selected by expert radiologists. Depending on the selected part ROI-mask is generated in such a way that the foreground is totally included and the pixel values in the background are made zero. The background regions though they appear to be black in colour, they do not have zero grey level values. Algorithm is implemented on a group of MR DICOM images. SPIHT is proved to 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 the image. Original image formatted in DICOM format of size 256 X 256 with 8 bit resolution is input to software. The „compressed image‟ is the image which is generated at the decoder side after reconstruction process. The output of encoder is a bit stream of numbers arranged in a manner so as to support the progressive transmission, with initial part as a ROI compressed with run length encoding. This bit stream is transmitted over the telemedicine network using GSM mobile device.

3.Medical image compression using wavelet decomposition for prediction method

Method is based on wavelet decomposition of the medical images followed by the correlation analyses are the basis of prediction equation for each sub band. Predictor variable selection is performed through coefficient graphic method to avoid multicolinearity problem and to achieve high prediction accuracy and compression rate. The method is applied on MRI and CT images. Two MRI and two CT gray scale standard test images as shown in figure 2 of size128*128 have been taken from world wide web for experiments and comparisons. MATLAB 7.0 has been used for the implementation of the proposed approach and results have been conducted on Pentium-1V, 3.20 GHz processor with a memory of 512 MB. BPP (Bits Per Pixel) metric is evaluated to compile compression result. Every image was decomposed into three scales with 10 wavelet sub bands.

Basics of wavelete 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 effected 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 basis 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

$$f(t)=\iint\gamma(s,r)\psi_{s,r}(t)\,dr\,ds \qquad (2)$$

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

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

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

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

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.

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

1. Harr 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	

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 1.

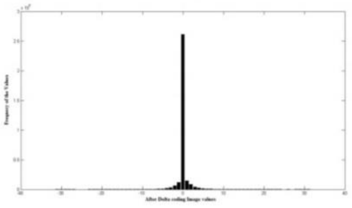
Even probability of losing important data of medical image is more in JPEG method. So a algorithm is proposed which contain the combination of basic techniques like Huffman coding, Predictive Delta coding, Bit plane slicing which provide sufficient CR (compression ratio) with better MSE, PSNR and CoC 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 2.

abdominal CT scan image (a) without Bit-plane slicing (b) with Bit-plane slicing

(a) (b)

The DM (Delta Modulation) model the difference between two consecutive pixel intensities is coded. Although the dynamic range of the difference signal is doubled as a result of differencing, the variance of difference signal is significantly reduced due to strong correlation typically present in the intensities of two pixels that are spatially close. We are calculating the difference of neighbourhood pixel value. Due to the strong correlation the difference between the pixels is less (probability high) and thus we can represent that value in low bits. These values are helpful for getting good compression in the case of Huffman coding as the probability of getting difference „0" is highest which is shown in Figure 3.

Frequency of Image Values after Delta coding for abdominal CT scam image



Huffman Coding is a variable length coding which has a strategy to minimise the average number of bits required for coding of a symbols by assigning shorter/longer length code to more/less probable symbol .It assigns a single bit to the most probable value and successively more bits to less probable values. The weighted sum of multiplication of number of bits for a particular value and probability of that value's occurrence in the frame yields the average bit size per value needed to transmit the frame. This number is less than or equal to the number of bits if each value was equally probable. As shown in step 2 the probability of occurrence of „0" is more so using Huffman coding we will assign less bits to it such that we can achieve good compression through it.

1 MSE(Mean Square Error)

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

$$\varepsilon = X - c$$

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 θ0 (instead of c). ε is called the "estimation error" of θ * . A good estimator is close to θ0 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 colour 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 colour images the image is converted to a different colour space and PSNR is reported against each channel of that colour 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 covary 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 covary 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).

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

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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