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Medical image Compression using Dwt Technique and its Optimization

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Abstract
Image compression is a significant technology in the storage and transmission of digital images since massive data is incorporated in all the related applications. As nowadays the entire globe is moving on the road to filmless imaging, Medical image compression has become one of the uncompromising requisite. One of the common and extensive technique used for Image compression is discrete wavelet transform (DWT). In this technique, the input signal is transformed into elementary frequency components. This paper depicts an optimized form of DWT implemented with MatLab programming and the efficiency is measured in terms PSNR, MSE, Entropy and SSIM

Keywords *—Lossless Image Compression, Medical Image Compression, MSE, PSNR, DWT*

1. INTRODUCTION

In the field of Computer science and information theory, data compression implies, encoding any digital information using fewer bits than the original representation and thus reducing the original file size. The vital feature of merit for data compression is the "compression ratio", which is the ratio of the size of a compressed file to the original uncompressed file. For example, suppose a data file takes up 30 kilobytes (KB). Using data compression techniques, the file could be reduced in size to, say, 15 KB that makes it easier to store on disk and helps faster transmission over an Internet connection. Thus the data compression software reduces the size of the data file in this case by a factor of two, and hence the "compression ratio" of 2:1 is attained. Obviously, the reduction in the file size ensures the reducedusage of the vital resources, such as storage space and transmission bandwidth.

In the discipline of Digital Image Processing, Image compressionis a principal issue to be handled very effectively. Extensively high quality images are produced by the gadgets available presently which in turn subsequently ends up in the need for considerably huge amount of storage space. Data compression techniques are very much essential in such a condition.

Image compression has its existence in several applications that requires is important for many applications that involve massive data storage and transmission of data such as videoconferencing files, medical images and multimedia files. In the medicine domain, need for Medical images is an absoluteworthy need. Each and every day bytes and bytes of medical imagedata are produced through advance imaging modalities such as X-rays,Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET) and still more advanced technologies.Nevertheless the consequence is the need for storing and transferring these colossal data.

Medical image compression is a chief area of telemedicine and biomedical domain. Image compression schemes can be broadly categorized into two types. One is lossless image compression which in other words is reversible compression. In this method, though the compression ratio achieved is slightly lesser, but the original image could be exactly reconstructed from the compressed image. On the other hand, the method, the lossy scheme which is the irreversible method of compression achieve higher compression ratio at the cost of loss of information in the compressed image ie., the reconstructed image will not be exactly the same as the original image.

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2. TYPES OF IMAGE COMPRESSION

Lossless Compression

In natural images, a high degree of correlation exists between the neighboring pixels.This statistical redundancy is exploited in lossless compression techniques in such away that the whole process is reversible and hence exactly theoriginal image could be retrieved; no information is lost in the compression process. This method of compression is also called as entropy coding. Lossless compression is used when it is very much imperative that the original and the decompressed image need to be identical, or when no assumption can be made and very high fidelity is expected. Typical examples are medical images, executable programs and source code

Lossy compression

When high compression ratio is expected, lossy compression techniques are to be applied. Lossy methods are particularly appropriate images where minor loss of fidelity is acceptable to attain a substantial reduction in bit rate. The imperceptible differences produced by lossy compression techniques are called visually lossless.Predictive coding, vector quantization, wavelet/subband,Transform coding, fractal coding are some of the categories of Lossy compression techniques.

3. OVERVIEW OF DISCRETE WAVELET TRANSFORM

A small wave that has itsenergy intensive in time is called a wavelet. It encompassesthe oscillating Wave-like properties neverthelesspossess the capabilityto permitconcurrent time and frequency analysistoo. In many fields of science and engineering, Wavelet Transform has developedas a mighty mathematicalinstrument,further more in the domainofdata and audio compression in particular.

Though DWT and Fourier series are very much similar, DWT is much more adaptable and informative. DWT acts as an instrumentthatsplits up the data into sub bands or distinctcomponents of frequency. It thenanalyzeseverycomponent with a resolution thatcorresponds to its scale. It can be applied on non-stationary transient signals with remarkablefindings which is in contrast to the Fourier series.

Information regardingthe localization of thefeatures of an audio signal is totallymissed in Fourier transform domain. Quality of the total audio file could be affected by the quantization error on one coefficient. A moreprecise local description and separation of signal characteristics is permitted by the wavelet expansion. A wavelet expansion coefficient denotesa component that by itself is local and is simpler to interpret. The Fourier basis functions have infinite support in that a single point in the Fourier domain contains information from everywhere in the signal.In contrast,Wavelets have compact or finite support and this makes it possible forvariousfractionsof a signal be denotedbyvarious resolution.

Wavelets can beproposedfor adaptive systems whichfine-tunethemselves in order to matchthe signal since they are adaptable and adjustable. Fourier Transform, however, is suitable only if the signal consists of a few stationary components. Also, the amplitude spectrum does not provide any idea about how the frequency evolve with time. All wavelets are likely tobe zero atinfinity that is enhanced already compared to the Fourier series function.Besides, wavelets can be formulatedto tend to zero as quickly as possible. Wavelets are muchefficient in audio andsignalcompression because of thisfeature.

A. Sub-band Coding

A signal is disseminated across a runs of filters to calculatethe signal's DWT. By means ofdeliveringthis signalvia a half band digital low pass filter with h(n) as the impulse response, the course of actioncommences.Filtering of a signal is numerically equal to convolution of the tile signal with impulse response of the filter.

All frequencies which are exceedinghalf of the maximumfrequency in the signal are eliminated by a half band low pass filter. Thenthrough the high pass filter, the signal is passed. The relation between the two filtersis expressed in the following equation:

$$h[L-1-n]=(-1)^n g(n)$$

Filters satisfying this condition are known as quadraturemirror filters. Half of the samples can beremoved after filtering,in view of the fact thathalf of the original frequency is now the highest frequency of the signal. The signal can thus be sub sampled by 2, justby sheddingevery other sample.

Asmerely half of the number of samplesportrays the entire signalnow, the time resolution is also halved by this decomposition. Nevertheless, frequency resolution has been doubled because half the frequency band of the input is comprised in each of the output. This process is termed as sub band coding. In order to

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intensifythe frequency resolution, this process of decomposition could be reiteratedstill further.

B. Compression Steps

- **Digitation**

The source image is digitizedinto a signal s that is a number string.The image is first digitized. The digitized image can bedescribedby two factors as - intensity levels which is nothing but the scales of gray that rangesfrom 0(black) to 255(white) and resolutionwhich describes about how many pixels per square inch is present.

- **Decompose the signal into a sequence of wavelet coefficients w.**

- **Thresholding**

To changethe wavelet coefficients from w tow',apply threshold.In certain signals, many of the wavelet coefficients are closeor equal to zero. By means ofthe use of threshold, these coefficients arealtered with the intention ofhaving thesequenceofwaveletcoefficients including long strings of zeros. In hard threshold, a threshold is selected. The wavelet is set to zero for whom the absolute value dropslesser than the tolerance, with the objective of initiating many zeros without the loss of a huge amount of detail.

- **Quantization**

In order to transformw' to a sequence q, apply quantization.A floating number sequence w' is converted to an integersequence q by means of Quantization. Rounding to the nearest integer is the trouble-freeform. Multiplyingevery number in w' by a constant k followed by rounding it to the nearest integer is an alternative method. Error is introducedinto thecourse, as the transformationof w' to q is not one to one function and hence the quantization is called lossy.

- **Entropy Coding**

To convert q into a sequence e, entropy encoding isemployed.In this method, the integer sequence q is transformedinto asmallersequence e, where the numbers in e being 8 bit integers. An entropy encoding table is used for the conversion. Numbers 1 through 100,105 and 106 are used to code the strings of zeros, whereas101 through104 and 107 through 254 are applied for codingthe non-zero integers in q.

4. ERROR METRICS

In this paper we introduce an optimized form of DWTand its efficiency is analyzed in terms of four different metrics as Peak-signal-to-Noise ratio (PSNR), Mean Square Error (MSE), Entropy, and Structural Similarity Index (SSIM)

1. PSNR-Peak Signal Noise Ratio: PSNR is the ratio between the maximum power of a signal and the noise corrupted signal that affects the reliability of the signal representation. To measure the quality of the image, this metric is applied. The high PSNR value denotes the reconstructed image quality is high, and the low PSNR value denotes the reconstructed image quality is low
   PSNR = 20 * log 10(255/sqrt (MSE))

2. Mean Square Error (MSE): MSE is the metric used to verify the mean square error of the image. The MSE is used to estimate the difference between two images in terms squared error value
   MSE =S(Sum (SquaredErrorImage)) / (rows x columns)

3. Entropy: is the corresponding intensity level states that could be adapted by individual pixels. It is used in quantitative image analysis of the image

4. Structural Similarity Index (SSIM) quantifies the degradation in quality of the image as a result of data compression. This metric requires two images from the same image capture ie., the reference image and the processed image, for the quality to be compared.

5. OPTIMIZED DWT

As DWT is one of the fittest algorithms to implement lossy image compression, it is taken as the source design and an optimization is carried out. The proposed algorithm is given below:

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Input: Medical images

Output: Optimized images

Im = I (j+1, m,n)

For each 2D image

Apply filter band

End for

Apply pass filter for optimized DWT

$\int_{-\infty}^{0} \Psi(t)dt = 0$

Estimation of min and max frequency

$\int_{-\infty}^{0} |\Psi(t)^2|dt < \infty$

Magnitude of the image is determined by

$f(I) = |H(e^{(jw)})|$

Bandwidth signal is halved

Filter divided into Low Pass Filter & High Pass Filter

1-D Downsampling in both Low pass filter and High pass filter is applied

1-D Filter bands with down sampling is applied in parallel

Level 1 Decomposition begin with LL,LH,HL,HH

Proposed factor of an image will be I(LL(j,m,n) I(LH(j,m,n) I(HL(j,m,n) I(HL(j,m,n)

I_{LL}(LL (j,m,n) => Approximation of an image passed in Low pass filter

I_{LH}(j.m.n)=> Horizontal Edges of input image

I_{HL}(j.m.n)=> Vertical Edges of an image

I_{HH}(j,m,n) => Diagonal Edge of an image

Level 2 Decomposition in LL subband

I_{LL}=> (j-1,m,n)

I(LL_1)(j-1,m, n) => Approximation of the image is passed through Low pass filter

I(LH_1)(j-1.m.n)=> Horizontal Edges of input image

I(HL_1)(j-1.m.n)=> Vertical Edges of an image

I (HH_1)(j-1,m,n) => Diagonal Edge of an image

Algorithm: Optimized DWT

In the newly developed scheme is used in six varied categories of images that are scan and x-ray image. In the initial process all the eight images were initialized for further process. In step 2, the filter bands are applied on 2D images. In step 3, the 2 pass filter which is a Low pass filter and High pass filter is applied on the input

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image. In step 4, the magnitude of the image is determined by the applied filter bands ie., $f(I)$ = ((max/2), ($H_0(z)$,$H_1(z)$)). In step 5, the minimum frequency max (f) and maximum frequency min (f) are acquired. In step 6, the bandwidth signal is halved. In step 7, the filter is divide in to low pass and high pass filters. In step 8, 1-D down sampling is applied in both Low pass and High pas filters. The Low pass filter is applied for the purpose of approximation of the image whereas the High pass filter, extracts the edges of the input image. In step 9, 1-D filter bands are also applied simultaneously with down sampling and this iteration continues until the rows and columns of the image ends. In step 10, level 1 decomposition of the image is executed. In step 11, the approximation of the input image, I_{LL}(LL (j,m,n)) is obtained through the low pass filter. From the high pass filter we obtainI_{LH}(j.m.n), I_{HL}(j.m.n) and I_{HH}(j,m,n) which are horizontal edge, vertical edge and diagonal edge of the image respectively. Level 1 decomposition is concluded with this output. Unless the actual DWT method in which the sub sampling is achieved by a factor of 2 with rows and columns of the image, the proposed method carries out the sub sampling process by a factor of 4. In step 12, level 2 decomposition is performed on the LL sub band as I_{LL}=> (j-1,m,n). In step 13, approximation of the image I(LL_1)(j-1,m,n) is extracted from the low pass filter. Likewise, the horizontal edge I(LH_1)(j-1.m.n), vertical edge I(HL_1)(j-1.m.n) and diagonal edge I(HH_1)(j-1,m,n) are acquired by passing through high pass filter. Thus in the proposed algorithm this process of iteration is carried out repeatedly and the efficiency is analyzed in terms of four different metrics

6. EXPERIMENTAL RESULTS

In this paper, an optimized form of DWT algorithm is proposed. The algorithm is implemented and the results are obtained by processing the medical images using Matlab. Fig 1 shows the test images applied for compression and Fig 2 gives the corresponding compressed images

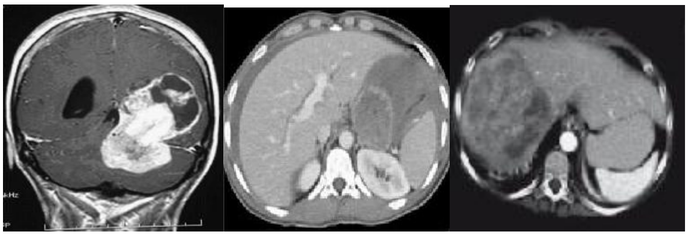

Image 1 Image 2 Image 3

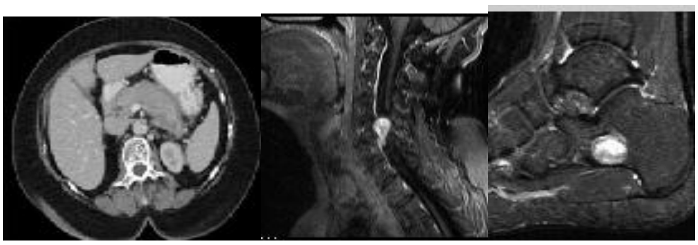

Image 4 Image 5 Image 6

Fig 1. Test Images

The above given medical images are subjected to the proposed compression algorithm and the images are compressed correspondingly as shown below:

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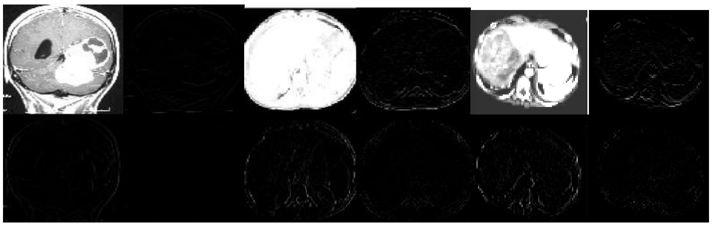

Image 1 Image 2 Image 3

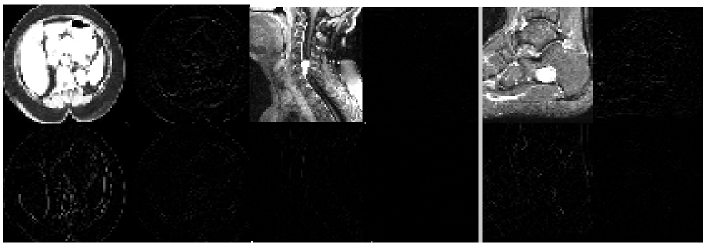

Image 4 Image 5 Image 6

Fig 2. Compressed Images

The experimental results by the proposed method with four different metrics as Peak-signal-to-Noise ratio (PSNR), Mean Square Error (MSE), Entropy, and Structural Similarity Index (SSIM) and the subsequent data are presented in the following table

TABLE I
METRICS FOR QUALITY ANALYSIS

IMAGE	PSNR	MSE	ENTROPY	SSIM
IM1	16.44	1.6	3.64	0.07
IM2	14.8	11.37	3.22	0.1
IM3	15.7	2.68	4.1	0.09
IM4	14.2	3	2.99	0.12
IM5	16.98	5.05	3.76	0.05
IM6	15.57	6.81	3.89	0.01

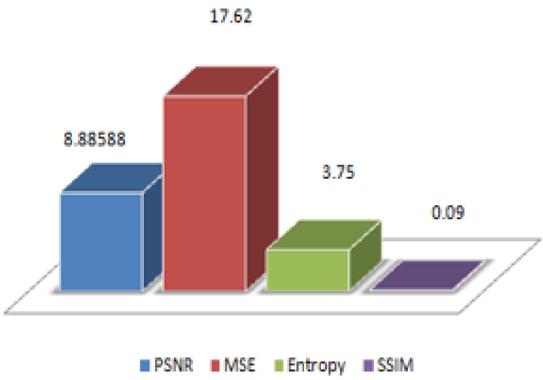

Fig 3.Metrics chart

Above chart clearly depicts the elevated efficiency with much increased PSNR and reduced values of all the other three metrics MSE, Entropy and SSIM

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7. CONCLUSION

Based on DWT algorithm a modified DWT technique is introduced in the proposed work for the medical image compression. The performance of the proposed approach is clearly proved and is shown in the above table and the chart. The experimental results depicts that better results are achieved which are approvingly efficient in terms of four different metrics. The efficiency of the approach is validated using real medical images set.

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