An Efficient Medical Image Compression Scheme

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Abstract— proposed technique is able to cope with medical image compression and restoration. Firstly it employs wavelet transforms that preserve the constructive of the medical image and image compression. Then, according to the reduction ratio demand, the sparse representation express the wavelet ratio. Experimental results show that the proposed algorithm is effective and compares favorably with existing techniques. With the development of the medical level and the economy, medical image plays an important role in clinic diagnoses. At first, more and more medical imaging equipment used in clinic, therefore, the medical image increasing rapidly. Moreover, long-distance medicine need medical image not too large to communication. But different from other images, medical image, with some important messages, is the basis to analyze the illness. Some damnify medicine information of image will lead to false diagnose. Therefore it is cautious to medical image compression.

Keywords— Compression, DCT, PSNR, Restoration

I. INTRODUCTION

Image compression is a field that is growing exponentially, due to its widespread applications in digital imaging and transmission. With the evolution of digital storage of visual information from grayscale still images to full-colour real-time video images, ever increasing bandwidths will be needed if very high compression ratio real-time image compression techniques were not available. Image compression serves to alleviate this problem by reducing the required bandwidths and allowing new applications, such as videoconferencing, to coexist with existing data and information transmission on computer networks. A gray scale image that is 256 x 256 pixels have 65, 536 elements to store and a typical 640 x 480 color image have nearly a million. Downloading of these files from internet can be very time consuming task. Image data comprise of a significant portion of the multimedia data and they occupy the major portion of the communication bandwidth for multimedia communication. Therefore development of efficient techniques for image compression has become quite necessary [1]. From biological studies, it has been determined that our visual and auditory senses perform some “masking” of the received inputs, rendering a portion of the received input redundant and unperceivable. This enables us to devise lossy data compression techniques which remove this redundant information, thus achieving much higher compression ratios. The rate distortion theory details the trade-off between achievable compression ratios and the resultant distortion incurred on the data source [1].

This is the rationale behind modern image compression techniques such as the JPEG still image compression scheme, which provides compression ratios of 5:1 to 20:1 with reasonable distortions. Nonetheless, most of these algorithms do not provide uses with much control over the specification of which components of the images are non-redundant, since the associated cost-functions are usually global in nature and affect the entire image or dataset. This presents a problem for applications such as the compression of magnetic resonance images, since not all image data is equally important for image interpretation and analysis.

Three performance metrics are used to evaluate algorithms and choose the most suitable one:
1) Compression ratio,
2) Computational requirements, and
3) Memory requirements.

Basically, the desired compression ratio is at least 2:1. The computational needs of an algorithm is expressed, in terms of how many operations (additions/multiplications, etc.) are required to encode a pixel (byte). The third metric is the amount of memory or buffer required to carry out an algorithm. CT or MRI Medical imaging [4] produces human body pictures in digital form.

The characteristics of an appropriate image compression scheme can be defined as follows:

(i) the ability to specify which components of the image are vital for visual integrity and contain the most information, and therefore, need to be preserved with very little or no loss.

(ii) The ability to achieve as high compression ratios as possible for the other portions of the image, leading to significant savings in transmission and storage requirements.

(iii) the need to control the distortion incurred by the high compression approach in (ii) to within user specified levels.

(iv) The ability to adapt to changes in the input data stream.

(v) The ability to perform the compression and decompression as fast as possible, for use in real-time applications.
Medical image compression, such as the compression of magnetic resonance images, requires the detection and recognition of boundaries in the tissue structures, for detection of lesions and tumours. This requires the preservation of edges in the image, which defines the various boundaries between the various anatomical structures and tissues in the image. In addition, the permissible distortion rate is zero to very low values for medical image compression due to its nature, resulting in a conflict between requirements (ii) and (iii), since distortion rate and achievable compression ratios are directly related (a high compression ratio implies a high distortion rate). Adaptation (requirement (iv)) is an offshoot of requirements (ii) and (iii), since a high compression ratio implies that the system is very efficient in its ability to convert uncompressed input into compressed output. Since actual data sources exhibit changes in their characteristics over time, adaptive compression schemes are necessary for maintaining the high compression ratios and specified distortion rates.

Many hospitals have satellite centres or clinics in small towns and remote areas to make it convenient for patients who have a hard time travelling the distance to the hospital, especially for diagnostic procedures. These hospitals make use of ‘teleradiology’ applications that allow the clinic staff to operate the clinic without the need for a radiologist to be present. Instead of a diagnostic radiologist, a technician or basic radiologist in the clinic can take the X-ray and send the image through a network connection to the hospital where the diagnostic radiologist can read the image and send back a diagnosis.

Most medical image compression algorithms are comprised of three main components, a decorrelation algorithm, a main compression engine and a formatting scheme.

\[
\text{Input Image} \xrightarrow{\text{Decorrelation algorithm}} \text{Compression engine} \xrightarrow{\text{Formatting scheme}} \text{Compressed bit - stream}
\]

Figure 1. Image Compression

Figure 1 shows general model of image compression where it is applied with input image where we get final compressed bit stream as shown.

II. RELATED WORK

The Joint Photographic Expert Group (JPEG) system, is the widely used scheme based on the Discrete Cosine Transform (DCT), used compression method [5][6]. The following are general steps for DCT compression

i) Original image is divided into blocks of 8 x 8.

ii) Pixel values of a black and white image range from 0-255 but DCT is designed to work on pixel values ranging from -128 to 127. Therefore each block is modified to work in the range.

iii) Equation (1) is used to calculate DCT matrix.

iv) DCT is applied to each block by multiplying the modified block with DCT matrix on the left and transpose of DCT matrix on its right.

v) Each block is then compressed through quantization.

vi) Quantized matrix is then entropy encoded.

vii) Compressed image is reconstructed through reverse process.

viii) Inverse DCT is used for decompression

Wavelets

No need to block the image
More robust under transmission errors
Facilitates progressive transmission of the image (Scalability)
This algorithm provides an optimal solution compression algorithm when only all the frequencies of every individual letters are used in order to compress the data. The DWT avoids the artifacts problem by operating on a complete image or a large part of an image. Consequently, it requires more memory than the DCT.

\[
\text{Input Image} \xrightarrow{\text{Volumetric image}} \xrightarrow{\text{Shape Coding}} \xrightarrow{\text{Shape Information}} \xrightarrow{(\text{Shape – adaptive/ ordinary}) 3D-DWT} \xrightarrow{\text{Scaling up of coefficient}} \xrightarrow{\text{3D-5PHIT}} \xrightarrow{\text{Code Stream}}
\]

Figure 2. Block Diagram of Shape Adaptive wavelet transforms

The ROI coding technique combines the feature of shape-adaptive wavelet transform and also provides scaling-based ROI, which we call SA-ROI [1]. In this method, the samples within the object are transformed with shape-adaptive wavelet transform according to the shape-information.

If required, the background is also must be transformed by well shape-adaptive wavelet transform independently and in
A discrete cosine transform (DCT) [7] in general generates sequence of finitely huge data points which are required in terms of a sum of cosine functions that are naturally oscillating at different frequencies. Discrete cosine transform is widely used in image and video compression applications such as JPEG and MPEG. These multimedia standards partition an input image into 8 × 8 blocks after that the DCT for each block is computed.

Later steps all the samples within the object are scaled up with certain amount of bit-shifts, and encoded plane by plane. In this case, the number of coefficients to be encoded does not change from the number of image samples within the object, and by scaling-up the coefficients of the object, the difference of image quality between the object and background can be controlled.

For each group of bits, individual probability model is used for dynamic arithmetic coding. The block-diagram of image decoding is presented in Figure 4 where IDCT denotes inverse DCT. Discrete Cosine Transform (DCT) has generally analyzed for the medical volumetric data coding but unfortunately fails to provide sufficient lossless coding that is coupled with quality and provide resolution scalability, which is more significant drawback for studying any medical application.

In addition, the DCT based compression standards are block-based causing blocking artifacts in the output image.

III. PROPOSED SYSTEM

To be more specific, consider an ideal procedure which consists in integrating the image intensity over columns; that is, along the orientation of our object. Unlike wavelet transforms, the ridgelet transform processes data by first computing integrals over lines with all kinds of orientations and locations.

Let I be the image with dimension of MXN, it is applied with the Gaussian filter which is applied for the denoising process.

\[ f(u,v) = e^{-\frac{(u^2+v^2)}{2\sigma^2}} \]  \hspace{1cm} \text{1}

\[ f_g(u,v) = \frac{f(u,v)}{\sum_{u,v} f} \]  \hspace{1cm} \text{2}

The eqn (1) and eqn (2) are the Gaussian filter which may be utilized for the denoising process. This Gaussian filter returns a rotationally symmetric Gaussian lowpass filter of size. \[ \sigma \] with standard deviation \[ \sigma \] (positive). After denoising the image using the Gaussian filter the denoised image is obtained. Wavelet transform partitions a signal into a set of functions called wavelets. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting. The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies.

A signal is passed through a series of filters to calculate DWT. Procedure starts by passing this signal sequence through a half band digital low pass filter with impulse response \( h(n) \). Filtering of a signal is numerically equal to convolution of the signal with impulse response of the filter. A half band low pass filter removes all frequencies that are above half of the highest frequency in the signal. Then the signal is passed through high pass filter.

1. Digitize the source image into a signal \( s \), which is a string of numbers.
2. Decompose the signal into a sequence of wavelet coefficients \( w \).
3. Use threshold to modify the wavelet coefficients from \( w \) to \( w' \).
4. Use quantization to convert \( w' \) to a sequence \( q \).
5. Entropy encoding is applied to convert \( q \) into a sequence e.
The following details the DWT process on the images and the following eqn details the 2D DWT process.

\[ H_i = \sum_{l=0}^{k-1} I_{dc_2r^1} \ast S_i(z) \] ……3

\[ L_i = \sum_{l=0}^{k-1} I_{dc_2r^1} \ast P_i(z) \] …….4

These are the high pass and low pass coefficients for the 2D DWT transform and the DWT coefficient vector is Dco. Subsequent to this process the finite ridgelet transform is applied on these coefficients. After obtaining these coefficients the image is then applied with the finite ridgelet transform.

When the FRIT coefficients r has been obtained now the compressed image has been obtained. For decompression the image has been applied with the inverse finite ridgelet transform initially the r of ridgelet transform coefficient is applied with the inverse FRIT. In the inverse FRIT the r is transformed to the radon domain and then the inverse finite radon transform has been obtained for it.

After that the inverse DWT has been applied on the image to obtain the original image of decompressed in size without losing of data. Hence our proposed hybrid technique compresses the image in an effective manner without degrading the image quality.

**ALGORITHM STEPS**

1) First Image is to be loaded in MATLAB using Image Acquisition. Image loading & resizing of image: In order to compress the image, the foremost step is to load the image and then the loaded image is resized into 256x256 formats so to reduce the compression time.

2) Discrete wavelet Transform: For the compression of image, firstly the DWT is applied on the image using the threshold value. On applying DWT one can obtain different levels of bands. Threshold values neglects the certain wavelet coefficients. For doing this one has to decide the value of threshold. Value of threshold affects the quality of compressed image.

3) Apply biorthogonal Ridgelet transform to obtain coefficients for compression. In this way, we have achieved a compressed image.

4) Calculation of CR, PSNR and MSE: After the image is compressed, last step is to calculate the CR, PSNR and MSE on different medical images.

5) To calculate CR Compression ratio is defined as the ratio of an original image to the compressed image CR=((original size-compressed size)/original size) *100;

6) To calculate PSNR Peak Signal –to-noise ratio this is defined as the ratio between the maximum achievable power of a signal or image to the power of the corrupting noise that deteriorates the fidelity of given representation.

**Performance**

The main objective of digital image compression is to reduce the size of digital images to save bandwidth or storage space and also transmission time. There are two techniques for doing this they are:

i) Lossless compression methods

\[ f(x, y) \] ---- Compression…. f(x,y) ,zero data loss, so they have 100% fidelity.

ii) Lossy compression methods

\[ f(x, y) \] ---- Compression…. \( f'(x,y) \), so some data loss, so they have fidelity is <100%.

Data compression is alternatively termed source coding for the case of lossless compression, since it entails finding the most compact representation of the data source. In general, lossless techniques are first generation techniques which utilize algorithmic approaches to compressing data. Lossy techniques usually adapt to the characteristics of the human visual system for determining what information is visually important.

**Error Metrics:** Two error metrics are used in order to compare various digital image compression techniques in nature they are:-

1. The Mean Square Error (MSE) and

2. The probalistic Signal to Noise Ratio (PSNR).

The MSE is the metric that is supposed to measure squared error between the compressed and the original digital image, on the other hand PSNR which measures the peak error in given image that can be mathematically written as

\[ \text{MSE} = \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} [I(x,y) - I'(x,y)]^2 \] ……5

\[ \text{PSNR} = 20 \times \log_{10} \left( \frac{255}{\text{sqrt(MSE)}} \right) \] ……6

Where I (x, y) is the original digital image, and I'(x, y) is the reconstructed image which is undergone through compression/decompression process and finally M, N are their dimensions of the images.

From the above discussions we can conclude that if we are having less MSE value than it shows that reconstructed image is less prone to noise and on other hand it should have PSNR to have more value that indicates signal or image quality is better resolution and secure.
RESULTS AND DISCUSSION

Reconstructing of digital image from the compressed data is generally easiest and a faster process than compare to compression process. The major steps involved are
1. Read in the quantized data from the file, using an entropy decoder.
2. Dequantize the data
3. Rebuild the image.

CONCLUSION

Compressive sensing is a new theory to capture the medical image signal, compared the traditional method, we propose a new technique for medical image compression and restoration. Wavelet transform used in this paper to image compression to constructive of the medical image. Experimental results show that our algorithm compares favorably in high-compressive ratio, the rapid processing speed and the preserve the characters of the image and determines the best compromise between compressed and reconstructed images.

REFERENCES

[4] Salih Burak Gokturk, Carlo Tomasi, Bernd Girod, Chris Beaulieu, “Medical image compression based on region of interest, with application to colon CT images”.
BIODATA

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