I J C T A, 9(26) 2016, pp. 193-200

Medical Image Compression Technique with Transform Method for Lung Cancer CT Scan Image: A Review

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ABSTRACT

The Medical image in their raw form wants an enormous amount of storage size. Considering the vital role played by medical imaging and, it is necessary to grow asystem that produces huge degree of imagecompression while preserving critical image information.There are several transformation techniques used for data compression. Karhunen-Loève Transform (KLT), Walsh-Hadamard Transform (WHT), Fast Fourier Transform (FFT), Sparse Fast Fourier Transform (SFFT), Discrete CosineTransform (DCT) and Discrete Wavelet Transform (DWT) are the most commonly usedtransformation.The results of simulation are compared different quality parameters of it are by applying on different lung cancer CT scan medical images. Like Compression Ratio (CR), Structural Content (SC), Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) compare to other Transform methods.

Keywords: Medical Image, Image compression, KLT, WHT, FFT SFFT, DCT, DWT, lung cancer CT images, CR, SC, MSE, PSNR.

1. INTRODUCTION

The medical Image compression is a process that focused on decreasing the size without losing quality, decrease the storage space of medical images and information of medical image. Lung cancer is the most common cause of cancer death in the world. Tobacco smoking cause's etiology breath and lung cancer. Patients at highly effected by the lung cancer [1]. In the case of an abnormal chest x-ray, the patient should directly undergo a chest CT scan for further evaluation. With the growth in Internet and multimedia technologies, the volume of information that is Controlled by computers has grown very fast. This information needs large volume of storage space and transmission bandwidth. One of the possible results to this problem is to compress the information so that the storage space and transmission time can be decreased. Main part of this Information that has to be stored and transmit contains images which have larger size. So image compression will resolve these issues regarding storage and transmission. Current years, advances in information technology and telecommunications have played a vital role as catalysts for Major developments in the sector of healthcare. Due to rapid rise in medical data made by hospitals and because of the high cost of provided that a large transmission bandwidth and enormous amount of storage space [2], compression of images is becoming progressively essential. The need of medical image compression is to Express images with fewer data to save storage space and transmission time, based on the ground that true information in the original image will be conserved.

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2. IMAGE COMPRESSION

2.1 Lossless *vs.* Lossy Compression

In lossless compression method, the rebuilt image, after compression, is numerically equal to the original image. However lossless compressions can only a reach a modest amount of compression. An image rebuilt following lossy compression covers degradation relation to the original [3]. Often this is because the compression method totally discards redundant information. However, lossy method are capable of Reaching much higher compression. Under normal inspecting conditions, no visible loss is Perceived (visually lossless).

2.2 Predictive *vs.* Transform Coding

In predictive coding, information previously sent or availableis used to predict upcoming values, and the variance is coded. Since this is done in the image orspatial domain, it is comparatively simple to implement and is readily adapted to the local image Characteristics [4]. The Differential Pulse Code Modulation (DPCM) is one particular example of the predictive coding. Transform coding is first transforms the image from its spatial domain illustration to a different type of representation using some well-known transform data andthen codes the transformed values (coefficients). This method provides more data compression compared to predictive methods, although at the expense of the more computation.

2.3 Lossy Image Compression

The Compression methods used in medical image applications are most of the time lossless scheme in order to preserved the data reliability and to facilitate the true diagnosis. However, lossless coding doesn'tallow the high compression ratios. Therefore, most of applications such as fast searching and telemedicine and browsing of medical volumetric image suffer from this limitation [5]. Though, lossy coding can reach higher compression. Among the existing compression methods, transform coding is one of the most effective approaches.A lossy compression method mainly consists of three major steps:

1. Transformation which is the step that provides rise to higher compression.
2. Quantization which is the important issue for lossy methods and it is the alternative between lossless andlossy methods. Quantization decreases the symbols used to represent the image.
3. Entropy encoding. The Quantized symbols are encoded using altered entropycoding algorithms, like Huffman encoding.

3. REVIEW OF IMAGE COMPRESSION METHODOLOGY

In this work we take different lung cancer CT scan image and using different image compression to compress image without loss. Walaa M. Abhd-Elhafiez et al. [10] said the compression analysis results have indicated that the performance of the suggested method is much better, where the constructed medical images are less distorted and compressed with higher factor. In this comparative analysis of image compression is done by seven transform methods [6], which are Karhunen-Loève Transform (KLT), Walsh-Hadamard Transform (WHT) , Sparse Fast Fourier Transform (SFFT), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT).

3.1 Karhunen-Loève Transform (KLT)

Hotelling transform also known as Karhunen-Loève Transform or KLT, minimizes MSE that is present between original (sub) image and (decompressed) reconstruction. Thus for any image KLT is the optimal information compaction transformation as well as for any number of retained coefficients. KLT basic functioning is dependent on image but, this however makes pre-computing impossible and hence this does not qualify it as a practical option suitable for image compression.

There are several applications where KLT has been widely used as in multi-spectral analysis of satellite-gathered images through the resulting spectral signature of imaged regions. Also there is significant data reduction that is attained while storing satellite images considering multi-spectral sets have been transformed to KLT space [7]. Recently KLT has been used to facilitate images in facial recognition. It is important to note that image set size is possibly much bigger in the subsequent two applications.

Let us take into consideration a sample set of real-valued images from an ensemble of images. Create vectors with the equivalent pixel taken from each of the images, *i.e.* if there are D images each of size $M \times N$ then form the column vectors $x_k = (x_{ij}^0, x_{ij}^1 \ldots x_{ij}^{D-1})^T$ for $k = 1, 2 \ldots MN - 1$, $i = 0, 1 \ldots M - 1$ and $j = 0, 1 \ldots N - 1$ (with superscript T representing the transpose). Calculate the sample mean vector using the formula $m_x = \frac{1}{M}\sum_{k=1}^{MN-1} x_k$. Use a computational formula to create the sample covariance matrix as $[C_x]u_k = \lambda_k uk$, $k = 0, 1, \ldots D - 1$ where $\{u_k]$ are the eigenvectors with associated eigenvalue set $\{\lambda_k\}$. The KLT kernel is a unitary matrix, $[V]$, whose columns, (arranged in descending order of eigenvalue amplitude), are used to transform each zero-meaned vector: $y_k = [V]^T (x_k - m_k)$

3.2 Walsh-Hadamard Transform (WHT)

Walsh system functions forms the very basis for Walsh transform. Walsh functions are orthogonal [8] and have only +1 and –1 values. In general, the Walsh transform can be generated by the Hadamard matrix as follows:

$$H_{2^k} = \begin{bmatrix} H_{2^{k-1}} & H_{2^{k-1}} \\ H_{2^{k-1}} & -H_{2^{k-1}} \end{bmatrix} \forall k = 1, 2 \ldots \propto H_1 = 1 \text{ for } k = 0 \qquad [11]$$

WHT here was employed to facilitate face as well as signature recognition as WHT coefficients output array comprises only of integer values, resultantly Hadamard transform thus becomes a quick transform, and implementation is feasible in O (N log N) additions as well as subtractions.

3.3 Fourier Transform

Fourier Transform (FT) is known to decompose image as two components: sinus and cosines. This implies that FT will transform any image from spatial to frequency domain respectively [9]. Fact is that any function can be precisely approximated using sum of infinite sinus and cosines functions [10], [11]. Fourier Transform essentially is a method to execute this. Mathematically a two dimensional images Fourier transform is:

$$F(k, 1) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i, j) e^{-i2\pi\left(\frac{k_i + l_j}{N}\right)} e^{ix} = \cos x + i \sin x \qquad [2]$$

Here f is the image value in its spatial domain and F in its frequency domain. Transformation results in complex numbers. This can be showing either using a real and complex image or using a magnitude and phase image. Though, in image processing algorithms it the magnitude image alone which is of interest as it has the information required regarding the geometric structures of the images. Nonetheless, in case there is a necessity to modify image in the particular forms what is required to retransform is the need to preserve both [12].

3.4 Fast Fourier Transform

The Fast Fourier Transform (FFT) algorithm was established by Carl Friedrich Gauss nearby 1805. The FFT is used to compute the Discrete Fourier Transform (DFT). The bigger size $M = N \times N$ matrix split into smaller size N's of DFT in the time domain. The new Radix-2 Decimation in Time (DIT) FFT is the effective and simplest method. It's also used to compute 2^n point DFT. In the FFT method the given weights are multiplied by indexes. The output should be the bit reverse form of the given input signal. The compound conjugate regularity is used to signify the imaginary part [13].

3.5 Sparse Fast Fourier Transform (SFFT)

For any algorithms which is used to compute DFT must take time at least proportional to its output size, and $\Omega(n)$. Most of the signals in frequency domain are sparse [14]. In general signal processing techniques many applications contain small value of Fourier coefficients or equal to zero. So the resultant DFT is approximately sparse. This is general in video, that is most of the coefficient are negligible. Images and videos are equally sparse. An efficient algorithm is needed to compute FFT for the signals that are sparse in frequency domain. SFFT computes k – sparse approximation, whose runtime depends upon k, the larger coefficient in the signal. This algorithm works in the process of identifying these k values by a filter G. G concentrates in both time and frequency. G is zero for all values except at a small number of time co-ordinates, and the Fourier Transform of $G(\hat{G})$ is negligible except at a small fraction value which is about $\frac{1}{k}$ of the frequency co-ordinates. Gaussian or Dolph-Chebyshev function convolved with a box-car function is used to identify the large coefficients in sFFT. Using this filter to find location and magnitude of the higher frequency component, parallel acceleration is achieved easily [15][16].

Previous sub-linear algorithms have a runtime which is a polynomial in k and log n^3. The fastest runtime of these algorithms will be

$$O(k^2 \log^c n) \text{ or } O(k \log^c n) \tag{3}$$

For some constants $C > 2$.

The key feature of sFFT is its simple structure. It has an efficient runtime with low big –0th Constant. For a typical case of n which is a power of 2, the run time is

$$O(\log n \sqrt{nk \log n}) \tag{4}$$

The implementation method and the working of sFFT with mathematical derivative. The research is made with 128 × 128 medical image to compression and decompression with Proposed sFFT and calculating PSNR, MSE, CR, SC.

3.5.1 Algorithm

The structure of the proposed method contains following steps:

Step 1: The research is made with FFT to compute the Fourier Transform in a MATLAB application.

Step 2: The execution of the FFT algorithm in MATLAB application.

Step 3: The research is made with SFFT to compute the Fourier Transform in a single array.

Step 4: The execution of the SFFT algorithm Coding is based on Matlab library function and header files.

Step 5: The development and implementation of SFFT algorithm for computing DFT should be $Y_k = \sum_{j=0}^{n-1} Xj\, e^{-2\pi jK\sqrt{-1}/n}$ [5], Here the value of $i = \sqrt{-1}$.

3.6 Discrete Cosine Transform

The Discrete Cosine Transform (DCT) is an orthogonal transform, its attempts to the de-correlate the medical image data. After the de-correlation each transform coefficient can be independently encoded without losing the compression efficiency [17]. The DCT transforms the signal from the spatial representation into the frequency representation. The DCT signify an image as a summation of sinusoids of the varying magnitudes and frequencies. DCT property is a typical image utmost of the visually substantial information about an image is focused in just few coefficients of DCT. Afterwards the computation of the DCT coefficients, they are regularized according to a quantization table with the different measures provided by the JPEG image standard computed by the psycho visual evidence. The Selection of quantization table affects the compression ratio and entropy. The value of quantization is inversely proportional to quality of reconstructed image. Its gives better compression ratio and better mean square error [18]. In a Quantization, the less significant frequencies are discarded, and then the maximum important frequencies that remain are used to recover the image in decomposition method. After quantization, the quantized coefficients are rearranged in the zigzag order for the further compressed by an effective lossy coding algorithm. DCT has several merits: (1) It has the ability to pack more information in least coefficients. (2) It decreases the block like appearance called the blocking artifact that outputs when margins between sub-images become visible [19].

An image is signified as the two dimensional matrix, the 2-D DCT is used to compute a DCT Coefficients of an image. The 2-D DCT for an NXN input order can be defined as follows [31]:

$$D(i,j)=\left(\frac{1}{\sqrt{2N}}\right)C(i)C(j)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}P\left(x,y\right)\times\cos\left(\frac{\left(2x+1\right)i\pi}{2N}\right)\cos\cos\left(\frac{\left(2y+1\right)j\pi}{2N}\right) \tag{6}$$

Where, $P(x, y)$ is the input matrix image $N \times N$, (x, y) are the coordinate of the matrix elements and (i, j) are the coordinate of the coefficients, and

$$C(u)=\begin{Bmatrix}\frac{1}{\sqrt{2}} & \text{if } u=0\\ 1 & \text{if } u>0\end{Bmatrix} \tag{7}$$

The reconstructed image is the computed by using the inverse DCT (IDCT) according to the

$$P(x,y)=\frac{1}{\sqrt{2N}}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}C(i)C(j)D(i,j)\times\cos\left(\frac{\left(2x+1\right)i\pi}{2N}\right)\cos\left(\frac{\left(2y+1\right)j\pi}{2N}\right) \tag{8}$$

3.7 Discrete Wavelet Transform

The wavelet can be made from a scaling function which describes its scaling properties [20]. The limit that the scaling functions important be orthogonal to its discrete conversions implies some mathematical conditions on them which are mentioned ubiquitously, *e.g.* the dilation equation

$$\varnothing(x)=\sum_{k=-\infty}^{\infty}a_k\varnothing(s_x-k) \tag{9}$$

Here S is a scaling factor. Furthermore, the area between the function essential be normalized and scaling function should be orthogonal to its integer translations, *i.e.*

$$\int_{-\infty}^{\infty}\varnothing(x)\varnothing\left(x+l\right)dx=\delta_{0,l} \tag{10}$$

After presenting some more conditions (as the limitations above don't produce a discrete solution) we can obtain results of all these calculations, the finite set of coefficients a_k that describe the scaling function and similarly the wavelet [21]. The wavelet is got from the scaling function as N. Here N is an even integer. The given set of wavelets then constructs an orthonormal basis which it uses to decompose the signal. The research is made with 128x128 medical image to compression and decompression with SFFT, DCT, DWT and calculating PSNR, MSE, CR, SC.

4. PERFORMANCE EVALUATION

4.1 Peak Signal to Noise Ratio (PSNR in dB)

PSNR called as Peak Signal-to-Noise Ratio. PSNR approximates image quality index, however on its own it does not have the capability of drawing a comparison between the features of two distinct images [22]. There is a possibility however that lower PSNR image may be considered as an image whose tone quality is comparatively better than one with a higher signal to noise ratio as denoted by equation (11) below:

$$PSNR = 10\log\frac{255^2}{MSE} \tag{11}$$

4.2 Mean Square Error (MSE)

Mean square error is a measure of image quality index. Large value of mean square basically implies that a poor quality image [23]. Mean Square Error called as MSE. Generally, it is a criterion that has been widely used and is representative of the classical error estimate as denoted by equation below:

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}(x_{j,k} - x'_{j,k})^2 \tag{12}$$

where M and N are the image dimensions.

4.3 COMPRESSION RATIO (CR)

Compression Ratio is the ratio of number bits required to represent the data before compression to the number of bits required to represent data after compression [24]. Increase of compression ratio causes more effective compression technique employed and vice versa.

$$CR(bpp) = \frac{\text{Number of coded bits}}{n \times m} \tag{13}$$

4.4 Structural Content (SC)

Structural content measure that is employed to draw a comparison between two images inherent in several small image patches and to determine the images have in common [25]. A comparison is drawn between patches by deploying 2D continuous wavelet that acts as a low level corner detector. Large value of structural content SC basically implies a poor quality image.

$$SC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N} x_{j,k}^2}{\sum_{j=1}^{M}\sum_{k=1}^{N} x'^2_{j,k}} \tag{14}$$

CONCLUSION

In this paper performed a survey on various compressing techniques. For the medical images [2] various compression algorithm like KLT, WHT, FFT, SFFT, DCT and DWT is found to be the best algorithm based on compression speed and compression ratio. For medical image sequences using DCT and DWT, the quality can be better and to avoid the coding loss and have high compression ratio. This paper discusses various measurement parameter like PSNR, CR, SC and MSE. These techniques propose a sole characteristic which is used to compress medical CT image but there are some drawbacks present in these methods. Hence the research is going on to overcome these disadvantages and also to enhance the rebuilt qualityof compressed image with high compression rate for medical images.

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