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Lossless Medical Image Compression Algorithm Using Orthogonal Moment Transforms

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Abstract—*With the development of CT, MRI, EBCT, SMRI etc, the scanning rate and distinguishing rate of imaging equipments are enhanced greatly. Using Compression techniques, medical images can be processed in deep degree by de-noising, enhancement, edge extraction etc, to make good use of the image information and improve diagnosis. Since medical images are in digital format, more time efficient and cost effective image compression technologies are to be developed to reduce mass volume of image data. This paper proposes the use of orthogonal moment transform for fast and higher compression rates. This method incorporates a simplified mathematical approach using sub block reconstruction scheme that eliminates numerical instabilities at higher moment orders. Hence Orthogonal Moment clearly performs better for both real digital images and graphically generated images.*

Keywords*: Image Coding, Discrete Tchebichef Moment Transform (TMT), Orthogonal Moment Functions, DCT Compression.*

1. INTRODUCTION

Modern Medical imaging tools has a great impact on diagnosis of diseases and preparation to surgery. As medical images has transformed to digital formats such as DICOM, optimal settings for image compression are needed to facilitate long-term mass storage requirements. Also, with the increasing use of medical imaging in clinical practice and the growing dimensions of data set, the management of digital medical image data sets requires high compression rates. Optimal medical image compression is defined as a degree of compression that decreases file size substantially by maintaining a degree of image distortion that is not clinically significant. In contrast to JPEG medical image compression model, moment functions are used for detailed image analysis as they provide better image representation and higher image quality. Image moments constitute an important feature extraction method (FEM) which helps to generate high discriminative features. Their ability to capture the particular characteristics of the described pattern, makes them suitable for image analysis, image watermarking, pattern recognition system (PRS),texture segmentation, monitoring crowds and image projection[1]. A new class of moment transform called Discrete Tchebichef Transform (DTT), derived from a discrete class of Tchebichef polynomials, is a orthonormal version of orthogonal moments. Owing to its low computational complexity, Tchebichef Moment Compression is scalable and portable to smaller computing devices like Personal digital assistances (PDA) and mobile phones. The major benefits of moment based compression are -1.It reduces the amplitude of image features and helps in precise restoration.2.It is completely robust to anti-noise, anti-lossy and anti-mirror operations.

2. ORTHOGONAL MOMENTS

In image processing applications, an image moment is defined as a particular weighted approximation of the image pixel intensities. Orthogonal moment functions are basically used in feature representation techniques for image reconstruction and object identification. Orthogonal moments are often preferred due to its ability to represent images with the minimum redundancy.

2.1 DEFINITION

Consider a General moment $M_{pq}^{(f)}$ of an image f(x, y), where p, q are non-negative and r = p + q is called the order of the moment, is defined as :

$$M_{pq}^{(f)} = \int\int p_{pq}\ (x,y) f(x,y) dxdy \qquad (1)$$

where $p_{00}(x, y)$, $p_{10}(x, y)$, . . . , $p_{kj}(x, y)$, . . . are polynomial basis functions defined on D. These set of cartesian moments following the orthogonality condition are called as orthogonal moments expressed mathematically - two functions y_m and y_n are orthogonal over an interval $a \le x \le b$ if :

$$\int y_m(x) y_n(x) dx = 0 \qquad m \neq n \qquad (2)$$

The orthogonality condition simplifies the reconstruction of the original image from the generated moment functions. The set of discrete orthogonal moment functions based on discrete Chebyshev polynomials have been successfully introduced as alternatives to continuous orthogonal moments[4].The computational aspects of Tchebichef moments are discussed below :

2.2 TCHEBICHEF MOMENTS

Let T_{mn} be defined as Tchebichef moments based on a discrete orthogonal polynomial set {tn(x)} specified directly on the image space [0, S–1].

$$T_{mn} = \frac{1}{\rho(m,s)\rho(n,s)} \sum_{i=0}^{S-1}\sum_{j=0}^{S-1} t_m(i)\, t_n(j)\, f(i,j) \qquad (3)$$

for m, n = 0, 1, 2, …, S −1.

The Tchebichef orthogonal polynomials set {tn(x)} are generated recursively with the following set of initial conditions as :

$t_0(x)=1$

$t_1(x)=\frac{2x+1-S}{S}$

The general Tchebichef orthogonal polynomial equation are :

$$t_n(x) = \frac{(2n-1)t_1(x)t_{n-1}(x)-(n-1)t_{n-2}(x)(1-\frac{(n-1)^2}{S^2})}{n} \quad (4)$$

for n = 2, 3, …, S–1.

The degree of the polynomial is defined by :

$$\beta(n, S)= S^n \qquad (5)$$

The squared-norm equation of tn(x) is given by **:**

$$\rho(n, S) = \sum \{t_i(x)\}^2 \qquad (6)$$

3. TMT COMPRESSION ALGORITHM

In the proposed compression algorithm, an RGB image is divided into equal sized blocks of image data and discrete Tchebichef moments are performed independently on each block. The quantization tables are proposed to reduce the high frequencies. Next, Huffman code is used to calculate the average bit length of TMT coefficient. TMT is implemented to achieve excellent compression performance. The visual TMT image compression is depicted in Fig. 1.

3.1 COLOR SPACE CONVERSION

In order to achieve good compression ratio, the correlation between the color components is lowered by converting the RGB image to YCbCr. The RGB image should be separated into a luminance (Y) and two chrominance (Cb and Cr). YCbCr can be computed directly from 8 bit RGB as follows:

$$\begin{pmatrix} Y \\ Cb \\ Cr \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ 0.1687 & -0.3313 & 0.5 \\ 0.5 & -0.4187 & -0.081 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} + \begin{pmatrix} 0 \\ 128 \\ 128 \end{pmatrix}$$

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1.4021 \\ 1 & -0.34414 & -0.71414 \\ 1 & 1.7718 & 0 \end{pmatrix} . \begin{pmatrix} Y \\ Cb \\ Cr \end{pmatrix} - \begin{pmatrix} 0 \\ 128 \\ 128 \end{pmatrix}$$

3.2 TMT

The image matrix are partitioned into 2x2 pixels where the orthogonal Tchebichef moments are calculated independently. The block size N is considered as 2.Based on orthogonal moments, a kernel matrix (K_{2X2}) is given as follows :

$$K = \begin{pmatrix} t(0) & t(1) \\ t(2) & t(3) \end{pmatrix}$$

The image block matrix (F_{2X2}) with [F(x, y)] denotes the intensity value of the pixel as :

$$\mathbf{F} = \begin{pmatrix} \boldsymbol{f(0,0)} & \boldsymbol{f(0,1)} \\ \boldsymbol{f(1,0)} & \boldsymbol{f(1,1)} \end{pmatrix}$$

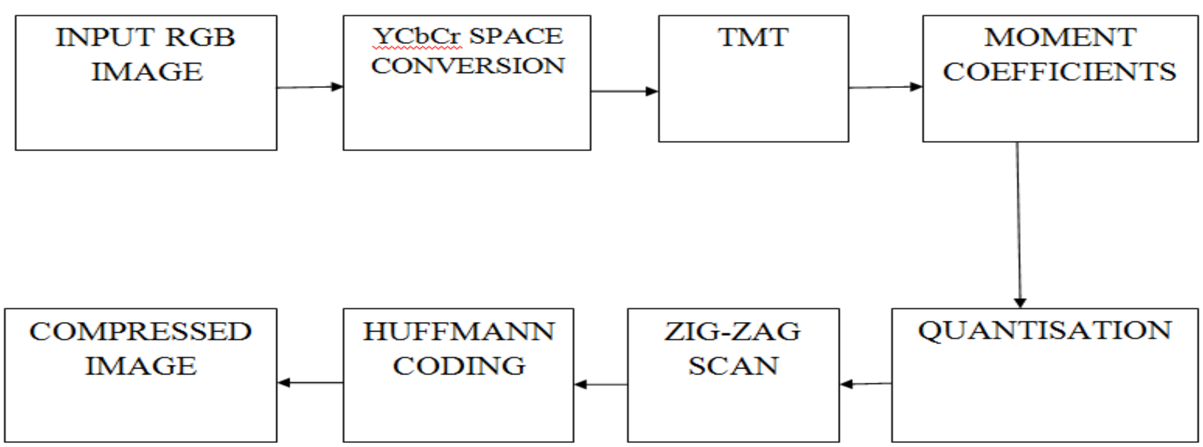

Fig. 1 BLOCK DIAGRAM OF PROPOSED ALGORITHM

3.3 QUANTIZATION

The idea of the quantization is to remove the high frequencies or discards information which is not visually significant. This is achieved by dividing the coefficient transform T(u,v) in each block using quantization matrix Q(u, v)[2].This process removes the high frequencies present in the original image and comprises a large number of zeroes as a result of the filtering of high frequency noise.

$$T_q(u,v)=Round((T(u,v)/Q(u,v)) \qquad (7)$$

3.4 ZIG-ZAG ORDERING

After the quantization technique, the coefficients are converted into a stream of binary data and the DC Coefficients are partitioned with the AC coefficients. All the coefficient in each sub-block is arranged in a zig-zag sequence and depicted as a linear array. The main purpose of the Zig-zag Scanning is to group low frequency coefficients in top of vector and it is quite optimal for lossless compression algorithms. The zig-zag output of quantized AC coefficient is represented as a series of data set. Next, run length encoding is used to minimise the size of a repeating coefficient value in the coefficient set.

3.5 HUFFMAN CODING

Huffman coding is a lossless coding technique to generate the shortest possible code length of the source symbol and the probability of occurrence of those symbols. Using these probability values, a set of Huffman code for the source symbols can be generated by Huffman Tree. The Huffman codes are saved in the Huffman Table. Huffman tables used during the compression process are stored as header information in the compressed image file in order to decode the coefficients asymmetrically during the decompression process. For image with three components, the encoder can store four sets of Huffman table (AC tables for Luminance and Chrominance and DC tables for Luminance ad Chrominance).

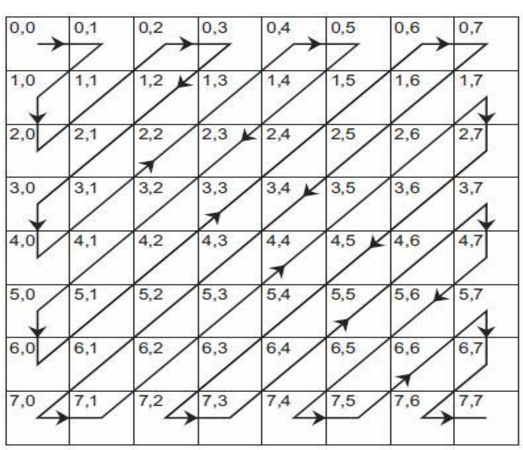

Fig.2 ZIG-ZAG SCANNING

3.6 IMAGE QUALITY MEASURES

The image reconstruction error can be calculated between reconstructed image g(i, j, k) and original image f(i, j, k) using :

$$E(s) = \frac{1}{3MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \sum_{k=0}^{2} \parallel g(\,i,j,k) - f(i,j,k) \parallel (8)$$

Other measurements that represents the reconstruction accuracy are Mean Squared Error (MSE) - calculates the average of the square of the error.

The MSE is defined as :

$$MSE = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \sum_{k=0}^{2} \parallel g(\,i,j,k) - f(i,j,k) \parallel^2 \quad (9)$$

Signal-to- Noise ratio (SNR) is used as a measure of quality of reconstruction and compression. The Peak SNR (PSNR) is defined as follows:

$$PSNR\ (dB) = 20 \log 10\ \frac{(Max_i)}{\sqrt{MSE}} \qquad (10)$$

where Max_i is the maximum possible pixel value.

AD is defined as the average difference occurred between original image and reconstructed image, while MD measures the maximum difference that occurred between the original image and reconstructed image. The formulas are defined as :

$$AD = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \sum_{k=0}^{R-1} \parallel I(i,j,k) \parallel \qquad (11)$$

$$MD = max_{0 \le i \le M} \parallel I(i,j,k) \parallel \qquad (12)$$

4. EXPERIMENTAL RESULTS

In this research, an efficient compression technique based on Discrete Tchebichef Transform (DTT) is proposed and developed. A set of test images are taken to justify the effectiveness of the algorithm. Fig.3 (a) shows the original image and Fig. 3(b) shows the reconstructed image. Fig.4 shows various stages of reconstruction where 5(a) and 5(b) refers to input image and initial 16x16 part of reconstruction. Fig 5(c) and 5(d) shows the 8x8 reconstruction and decompressed images. Table 1 depicts the quality measurements of various test images. Fig.5 shows the comparison of SNR of various input images. From this graph, it can be analyzed that higher SNR values result in higher compression performance.

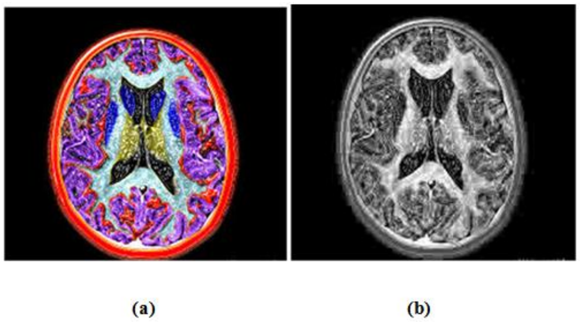

Fig. 3: ORIGINAL AND RECONSTRUCTED IMAGE

Table 1. IMAGE QUALITY MEASURES

PARAMETERS	IMAGE 1	IMAGE 2	IMAGE 3
PSNR	14.1912	13.2848	11.1682
MSE	43.5257	54.1624	70.4904
MD	222.1475	249.0821	249.0485

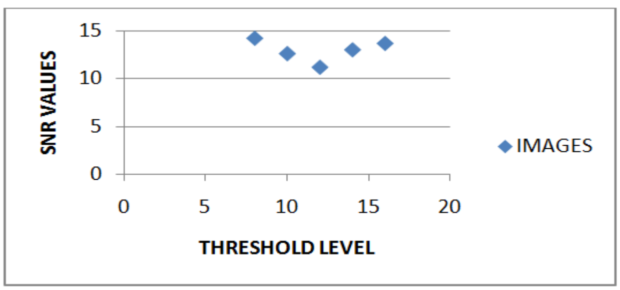

Fig. 4. COMPARISON OF SNR

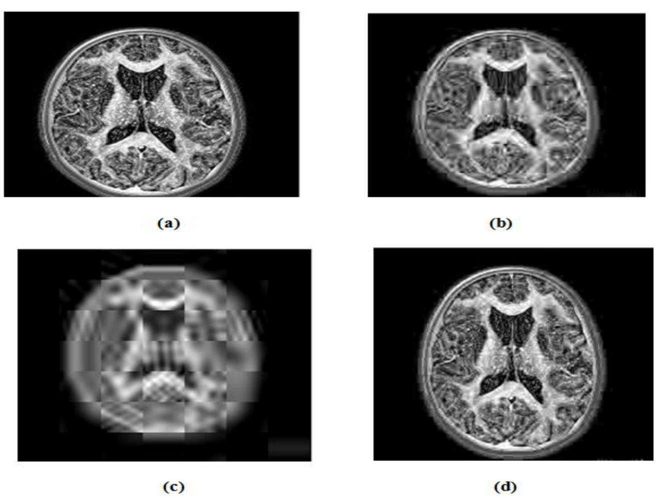

Fig.5 STAGES OF RECONSTRUCTION

5. CONCLUSION

The function of Tchebichef Moment Transform (TMT) can be used as an equivalent to DCT for applications in image compression and reconstruction. The set of Tchebichef Polynomials has the potential to work better for both real world imagery and high end graphics. Two important features of Tchebichef moments are identified: i. a discrete dimensionality of definition which matches exactly with the image coordinate, and ii. absence of numerical approximation errors for better reconstruction. The experimental results also prove that the proposed algorithm reduces the time taken to transform images of different sizes efficiently. Concurrently, it has lower computational complexity since it does not require any special primitive algorithms as JPEG Compression. This improvement makes it practical and a more elementary implementation for both software and hardware developers. The future approach of this research is to implement a similar compression technique using Legendre Moments which generates custom quantization tables for low, medium and high image output quality levels. The extended model allows a developer to design several customized quantization tables for a user to choose from according to target output specifications.

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