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An Optimal Tchebichef Moment Quantization using Psychovisual Threshold for Image Compression

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Colour image carries a certain amount of perceptual redundancy for the human eyes. The human eye is capable of perceiving various levels of colours. The sensitivity of human eye is useful for perceptual visual quality image in image compression. The visual sensitivity of the colour image in terms of image compression can be measured by a psychovisual threshold to generate the quantization tables. This paper will investigate a psychovisual threshold level for Tchebichef moment transform (TMT) from the contribution of its moments. In this paper presents a new technique to generate quantization table for TMT image compression based on psychovisual error threshold. The experimental results show that these new finer quantization tables based on psychovisual threshold for TMT provides better quality image and lower average bit length of Huffman code than previously proposed TMT quantization.

Keywords: TMT Quantization, Psychovisual Threshold, TMT Image Compression.

1. INTRODUCTION

The human eye has limited sensitivity to receive the visual information. The colour images possess a certain amount of perceptual redundancy[1]. The human visual system describes the way of human eye's process toward image and how to relays it to the brain. By taking the advantages of some human eye's properties, data redundancy can be removed without seriously degrading the image quality. In general, the human eye is more sensitive to luminance component of the image. The human eye has a non-linier response toward the drastic changes in intensity level and likely to be processed in different frequency channels[2]. The objective of this research is to develop quantitative measures that can automatically predict perceptual image quality[3]. In general, a psychovisual model has been designed based on our understanding of brain theory and neuroscience[4], which is used to determine a threshold of human visual system's sensitivity.

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This research proposes a model represented by a visual threshold based on Tchebichef moment by evaluating the image reconstruction. This experiment can be done by investigating the effect of incrementing TMT coefficient one by one. The effect of an increment in TMT coefficient is calculated and analyzed to get psychovisual threshold on the output image. This approach is used to generate quantization tables for TMT image compression.

The Tchebichef Moments Transform (TMT) is an efficient transform based on discrete Tchebichef polynomials[5]. TMT provides good energy compaction properties and works better for a certain class of images[6]. TMT has been shown to have better image representation capability than the continuous orthogonal moments[7]. TMT has been widely used in various image processing applications. For examples, they are used in image analysis[5], texture segmentation, multispectral texture, image reconstruction[8], image dithering[9,10] and image compression[11,12].

The organization of this paper is as follows. The next section provides a brief description of Tchebichef moment transform. Section 3 presents the experimental method in generating psychovisual threshold. The experimental results of TMT image compression based on new quantization table from psychovisual threshold are presented in Section 4. Lastly section 5 concludes this paper.

2. TCHEBICHEF MOMENT TRANSFORM

TMT is a two-dimensional transform based on discrete orthogonal Tchebichef polynomials[3]. For a given set $\{t_n(x)\}$ of input value (image intensity values) of size N=8, the forward TMT of order $m + n$ is given as follows[5]:

$$T_{mn} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \frac{t_m(x)}{\rho(m,M)} f(x,y) \frac{t_n(y)}{\rho(n,N)}$$

$$T_{mn} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} k_m(x) f(x,y) k_n(y)$$

for m, n = 0, 1, 2, ..., N-1.

where $f(x, y)$ denotes the intensity value at the pixel position (x, y) in the image. The $t_n(x)$ are defined using the following recursive relation:

$$t_0(x) = 1,$$

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

$$t_n(x) = \frac{(2n-1)\cdot t_1(x)\cdot t_{n-1}(x) - (n-1)\left(1-\frac{(n-1)^2}{N^2}\right)\cdot t_{n-2}(x)}{n}$$

for n = 2, 3, ..., N-1. The first four discrete orthogonal Tchebichef moment transform is shown in Figure 1.

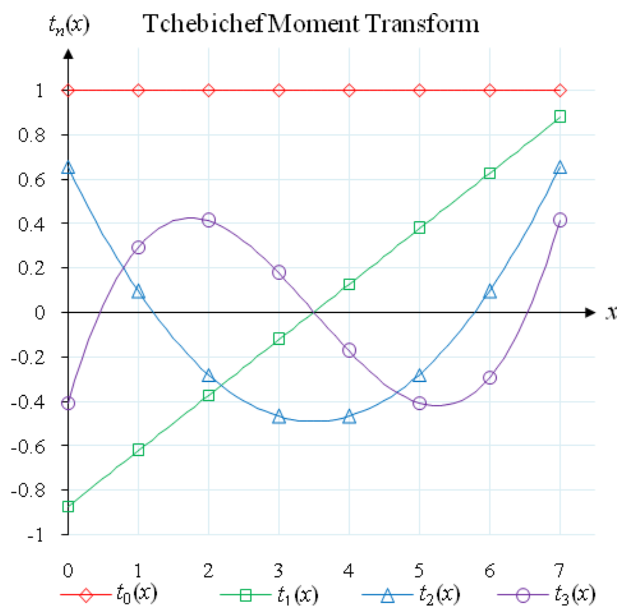

Fig. 1. The discrete orthogonal Tchebichef moments $t_n(x)$ for n = 0, 1, 2 and 3.

The above definition uses the following scale factor for the polynomial of degree n.

$$\beta(n, N) = N^n$$

The set $\{t_n(x)\}$ has a squared-norm given by

$$\rho(n,N) = \sum_{i=0}^{N-1} \{t_i(x)\}^2$$

$$= \frac{N\cdot\left(1-\frac{1^2}{N^2}\right)\cdot\left(1-\frac{2^2}{N^2}\right)\cdot\left(1-\frac{3^2}{N^2}\right)\cdots\left(1-\frac{n^2}{N^2}\right)}{2n+1}$$

The process of image reconstruction from its moments, the inverse TMT is given as follows:

$$\tilde{f}(x,y) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} k_m(x) T_{mn} k_n(y)$$

where M denotes the maximum order of moments being used and $\tilde{f}(x,y)$ denote the reconstructed intensity distribution.

3. AN EXPERIMENTAL METHOD

In this quantitative experimental, 80 images (24-bit RGB with 512×512 pixels) are chosen to be tested and analyzed. The images are classified into 40 real images and 40 graphical images respectively. The RGB image is separated into a luminance (Y) and two chrominance (U and V). The images are divided into the 8×8 size blocks and each block of the image data is transformed by a two-dimensional TMT. Next, the resulting moment coefficients are incremented one by one. The effect of an increment on moment coefficients to the images is measured by the error reconstruction. Based on the discrete orthogonal moments above, a compact representation of the moment coefficient $K_{(S\times S)}$ is given as follows:

$$K = \begin{bmatrix} k_0(0) & k_1(0) & \cdots & k_{S-1}(0) \\ k_0(1) & k_1(1) & \cdots & k_{S-1}(1) \\ k_0(2) & k_1(2) & \cdots & k_{S-1}(2) \\ \vdots & \vdots & \ddots & \vdots \\ k_0(S-1) & k_1(S-1) & \cdots & k_{S-1}(S-1) \end{bmatrix}$$

The image block matrix by $F_{(8\times8)}$ with $f(x, y)$ denotes the intensity value of the image pixels for each colour component:

$$F = \begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0,S-1) \\ f(1,0) & f(1,1) & \cdots & f(1,S-1) \\ f(2,0) & f(2,1) & \cdots & f(2,S-1) \\ \vdots & \vdots & \ddots & \vdots \\ f(S-1,0) & f(S-1,1) & \cdots & f(S-1,S-1) \end{bmatrix}$$

The matrix $T_{(S\times S)}$ of moments is defined using S=8 in above as follows:

$$T_{(8\times8)} = K^T_{(8\times8)} F_{(8\times8)} K_{(8\times8)}$$

This process is repeated for every block in the original image to generate coefficient of discrete orthogonal TMT. The inverse moment relation used to reconstruct the image block from the above moments and is as follows:

$$G_{(8\times8)} = K_{(8\times8)} T_{(8\times8)} K^T_{(8\times8)}$$

where $G_{(8\times8)}$ denotes the matrix image of the reconstructed intensity value. This process is repeated for 8×8 block of an image. The visual representation of the matrix is given in Figure 2.

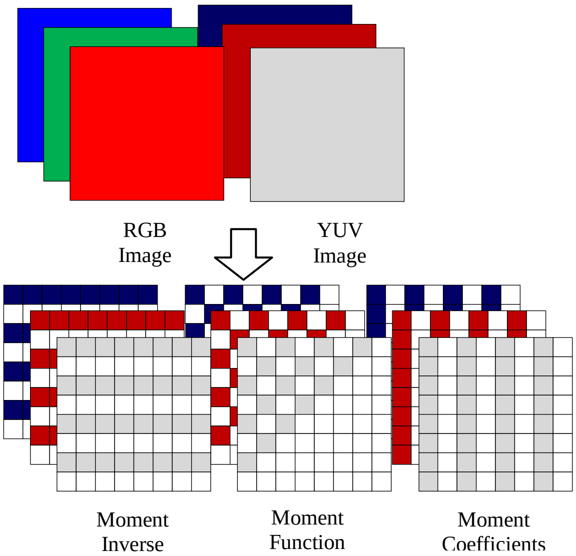

Fig. 2. Visual representation of the block matrices.

The use of moments for image analysis is to characterize an image segment and to extract properties that have analogies in statistics and mechanics. Each 8×8 block image is arranged in a linear order of the moment coefficient. The implementation of moment order by $M_{(S\times S)}$ where S=8 for TMT is as provided below:

$$M = \begin{bmatrix} m_{(0,0)} & m_{(0,1)} & \cdots & m_{(0,S-1)} \\ m_{(1,0)} & m_{(1,1)} & \cdots & m_{(1,S-1)} \\ m_{(2,0)} & m_{(2,1)} & \cdots & m_{(2,S-1)} \\ \vdots & \vdots & \ddots & \vdots \\ m_{(S-1,0)} & m_{(S-1,1)} & \cdots & m_{(S-1,S-1)} \end{bmatrix}$$

The order zero $m_{(0,0)}$ on moment coefficient represents the average intensity of an image. The first order on moment coefficients are represented by $m_{(1,0)}$ and $m_{(0,1)}$ coordinates. The second order of moment coefficients are located by ($m_{(2,0)}$, $m_{(1,1)}$ and $m_{(0,2)}$) coordinates. Moment coefficients are incremented up to a maximum of quantization tables for each moment order. The TMT quantization tables[13] are used as a reference for a maximum of an increment moment coefficients. The quantization tables for luminance Q_{ML} and chrominance Q_{MR} on TMT have been originally proposed as follows:

$$Q_{ML} = \begin{bmatrix} 4 & 4 & 4 & 8 & 16 & 24 & 40 & 64 \\ 4 & 4 & 8 & 16 & 24 & 40 & 64 & 128 \\ 4 & 8 & 16 & 24 & 40 & 64 & 128 & 128 \\ 8 & 16 & 24 & 40 & 64 & 128 & 128 & 256 \\ 16 & 24 & 40 & 64 & 128 & 128 & 256 & 256 \\ 24 & 40 & 64 & 128 & 128 & 256 & 256 & 128 \\ 40 & 64 & 128 & 128 & 256 & 256 & 128 & 128 \\ 64 & 128 & 128 & 256 & 256 & 128 & 128 & 64 \end{bmatrix}$$

$$Q_{MR} = \begin{bmatrix} 4 & 4 & 4 & 8 & 16 & 32 & 64 & 128 \\ 4 & 4 & 8 & 16 & 32 & 64 & 128 & 256 \\ 4 & 8 & 16 & 32 & 64 & 128 & 256 & 256 \\ 8 & 16 & 32 & 64 & 128 & 256 & 256 & 256 \\ 16 & 32 & 64 & 128 & 256 & 256 & 256 & 256 \\ 32 & 64 & 128 & 256 & 256 & 256 & 256 & 256 \\ 64 & 128 & 256 & 256 & 256 & 256 & 256 & 256 \\ 128 & 256 & 256 & 256 & 256 & 256 & 256 & 256 \end{bmatrix}$$

4. AN EXPERIMENTAL RESULTS

The effect of incremented moment coefficient is calculated by image reconstruction error measurement. The average reconstruction error of an increment moment coefficient on luminance (Y) and Chrominance (U) for 40 natural images are shown in Figure 3 and Figure 4.

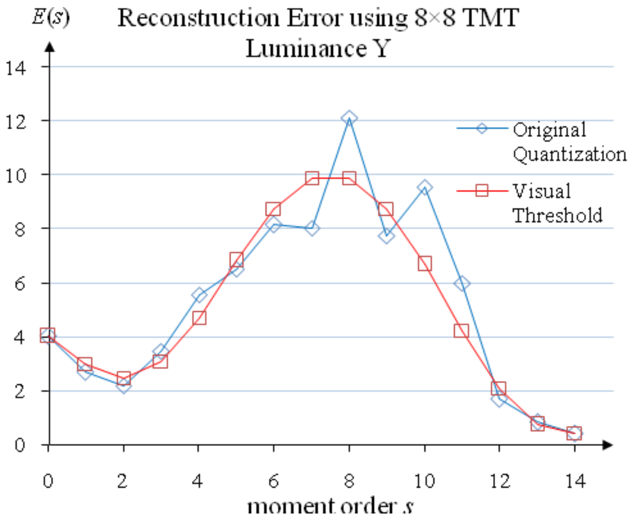

Fig. 3. Average reconstruction error of an increment on TMT coefficient for 40 natural color images.

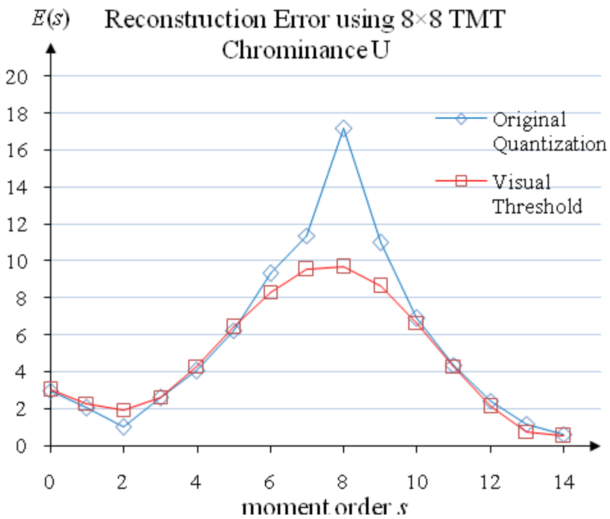

Fig. 4. Average reconstruction error of an increment on TMT coefficient for 40 natural color images.

The x-axis represents moment order and y-axis represents error reconstruction while the blue curve represents image reconstruction error based on a maximum quantization table value. The effect of an increment for each order shall produce a curve from zero to fourteen orders. In order to produce a psychovisual threshold, the new average designed reconstruction error is to get a smoothed curve which results in an ideal curve of average error scores. An ideal psychovisual threshold for luminance and chrominance is represented by a red curve. With reference to Figure 3 and Figure 4, the authors propose a psychovisual threshold for TMT basis function for luminance f_{ML} and chrominance f_{MR} of quantization table which are defined as follows:

$$f_{ML}(x) = -0.00009895x^6 + 0.0045x^5 - 0.07129x^4 + 0.4354x^3 - 0.6352x^2 - 0.737x + 4$$

$$f_{MR}(x) = -0.00008837x^6 + 0.0041x^5 - 0.0661x^4 + 0.4111x^3 - 0.6368x^2 - 0.4389x + 3$$

for x=0, 1, 2, ..., 14. According to equation above, these functions can be used to generate new quantization tables for luminance and chrominance respectively as follows:

$$Q_{VML} = \begin{bmatrix} 4 & 4 & 5 & 7 & 14 & 25 & 43 & 79 \\ 4 & 5 & 7 & 14 & 25 & 43 & 79 & 104 \\ 5 & 7 & 14 & 25 & 43 & 79 & 104 & 144 \\ 7 & 14 & 25 & 43 & 79 & 104 & 144 & 178 \\ 14 & 25 & 43 & 79 & 104 & 144 & 178 & 180 \\ 25 & 43 & 79 & 104 & 144 & 178 & 180 & 161 \\ 43 & 79 & 104 & 144 & 178 & 180 & 161 & 107 \\ 79 & 104 & 144 & 178 & 180 & 161 & 107 & 61 \end{bmatrix}$$

$$Q_{VMR} = \begin{bmatrix} 4 & 4 & 5 & 8 & 17 & 33 & 57 & 107 \\ 4 & 5 & 8 & 17 & 33 & 57 & 107 & 142 \\ 5 & 8 & 17 & 33 & 57 & 107 & 142 & 199 \\ 8 & 17 & 33 & 57 & 107 & 142 & 199 & 247 \\ 17 & 33 & 57 & 107 & 142 & 199 & 247 & 250 \\ 33 & 57 & 107 & 142 & 199 & 247 & 250 & 218 \\ 57 & 107 & 142 & 199 & 247 & 250 & 218 & 117 \\ 107 & 142 & 199 & 247 & 250 & 218 & 117 & 71 \end{bmatrix}$$

These new quantization tables will be applied in TMT image compression to measure the performance of the newly proposed visual threshold. Each element of the moment coefficient is divided by the corresponding elements in an 8×8 quantization table and rounding the results. After the transformation and quantization of an 8×8 image sub-block is over, the DC coefficient is separated from the AC coefficients. Next, run length encoding is used to reduce the size of a repeating coefficient value in the sequence of a set of AC coefficients data.

Table.1. Average Bit Length of Huffman Code on TMT Image Compression for 40 Real Images

Image Measurement	TMT quantization tables	psychovisual threshold
DC Luminance Y	4.7660	4.7660
DC Chrominance U	2.0237	2.0237
AC Luminance Y	1.7679	1.7642
AC Chrominance U	1.2124	1.1665

Table.2. Average Bit Length of Huffman Code on Image Compression Using TMT for 40 Graphical Images

Image Measurement	TMT quantization tables	psychovisual threshold
DC Luminance Y	4.9000	4.9000
DC Chrominance U	3.2357	3.2357
AC Luminance Y	2.3588	2.3554
AC Chrominance U	2.0027	1.7544

The coefficient value can be represented compactly by simply indicating the coefficient value and the length of its run wherever it appears. The output of run length coding represents a TMT coefficient as symbols and the length of occurrence of the symbols. The symbols and variable length of occurrence are used in Huffman coding to retrieve code words and their length of code words. Next, the average bit length score is calculated to find the average bit length of DC and AC coefficients. The average bit length newly of image compression based on default quantization and the proposed quantization based on psychovisual threshold for TMT are shown in Table 1 and Table 2.

The quality of image reconstruction based on new quantization table for TMT image compression is shown in Table 3 and Table 4. The image reconstruction error can be defined as follows:

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

where the original image size is $M \times N$ and the third index refers to the value of three colors of RGB channels.

Table.3. Average Image Reconstruction Error Score for 8×8 TMT on 40 Real Images

Image Measurement	TMT quantization tables	psychovisual threshold
Full Error	5.2584	5.2456
MSE	58.1587	57.4476
PSNR	31.3721	31.3790

Table.4. Average Image Reconstruction Error Score for 8×8 TMT on 40 Graphical Images

Image Measurement	TMT quantization tables	psychovisual threshold
Full Error	4.71429	4.6034
MSE	68.20336	62.5664
PSNR	31.4483	31.6477

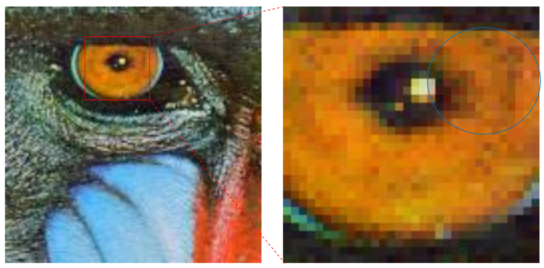

Fig. 5. Original color image (left) and zoomed in to 400% (right).

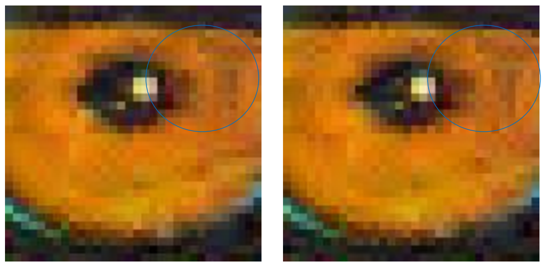

Fig. 6. The comparison between TMT quantization table (left) and psychovisual threshold quantization table for TMT (right) zoomed in to 400%.

In this experiment, the right eye of the baboon image is evaluated as presented on the left of Figure 5. In order to observe the visual quality of the image compression results, the image reconstruction is zoomed in to 400% as shown on the right of Figure 5. The experimental results of image compression using new quantization tables based on psychovisual threshold are shown on the right of Figure 6. The new quantization tables based on psychovisual threshold produces better quality image output than previously proposed TMT quantization tables[13] for TMT image compression.

The observation as presented on the right of Figure 6 point out the fact that the new quantization tables based on psychovisual threshold produce almost the same as the original image on the right of Figure 5. In addition, the image output produces smooth texture as pointed inside of blue circle. The experimental results show that the TMT quantization tables based on psychovisual threshold produces lower average bit length of Huffman code by resulting in Table 1 and Table 2 than the earlier TMT image compression for both real and graphical images.

Image compression using psychovisual threshold produce better quality reconstruction image as shown in Table 3 and Table 4 than previous TMT image compression[13]. It has been observed from the experiment, the error reconstruction from TMT basis function is relatively equally distributed among the orders of image signals. The new technique quantization table generation based on psychovisual threshold produces high quality image reconstruction at lower average bit length of Huffman code on image compression.

5. CONCLUSIONS

The psychovisual threshold represents the human visual system's sensitivity on the image intensity in term of image compression. The contribution of each frequency coefficient to the error reconstruction will be a primitive pyschovisual error. The psychovisual threshold appears in the value of the quantization table to assign the value of each frequency coefficient. This paper proposes a new technique to generate quantization tables based on psychovisual error threshold. This approach has been tested on TMT image compression. The new TMT quantization tables based on psychovisual threshold produces better quality image reconstruction at lower average bit length of Huffman code of the image compression than previously TMT quantization tables.

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