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A Fast Image Compression Scheme with Transcoding of Orthogonal Polynomials Coefficients

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Abstract: *A simple and fast image coding scheme with orthogonal polynomials transform and lifting scheme is proposed in this paper. The input images are first partitioned into number of blocks and orthogonal polynomials transformation is applied onto these blocks. These blocks of transform coefficients are reduced to half of its size with lifting scheme. The resultant transcoded coefficients are subjected to quantization scheme as in JPEG and then entropy coded with Huffman coding and variable length coding, which takes reduced time for dictionary look-up. The proposed image compression scheme with transcoded orthogonal polynomials coefficients is experimented on standard natural images and open source images and the performance of the proposed scheme is measured with peak signal to noise ratio and mean square error.*
Keywords: *Image compression, orthogonal polynomials, transcoded coefficients*

I. Introduction

In the recent decades, image compression has taken a good shape because of its application to image and video communications. The generic image compression process aims to reduce the total number of bits required to transmit or store the image. Basically there are two types of compression schemes: lossless or error–free and lossy. In lossless compression, the exact original in obtained after the compression–decompression process, but with lesser compression ratio. In the lossy compression scheme, there shall be some distortion in the quality of reconstructed picture but with higher compression ratio. The type of compression required also stems from the application point of view.

Even though there are many cases where loss of information is not tolerable such as medical, prepress, scientific and artistic images, lossy compression schemes have obtained popularity due to their large memory or bandwith requirements. The International standards Joint Photographers Experts Group [1] for still image compression and Motion Pictures Experts Group (MPEG) [2] for video compression have taken popularity with lossy compression. These standards use unitary transform namely Discrete Cosine Transform (DCT) to decorrelate the original signals. The JPEG2000 [3] standard uses Discrete Wavelet Transform for the same purpose. Besides coding, transform domain signal processing has variety of practical applications like scrambling, adaptive filtering etc [4]. In the case of transform coding the signal under analysis is represented as a linear combination of transform basis functions and the coefficients of such a combination are known as transform coefficients. These coefficients are then applied with quantization and entropy coding to propose the signal compression [5]. Besides DCT [6], other transforms such as Fourier Transform [7], Hadamard transform [8], Karhunan-Loeve Transform [9] and Wavelet Transform [10] are also reported to propose transform coding schemes in early years.

Among these transforms, DCT with its variation [11, 12, and 13] are reported in different methods of achieving compression. But computational complexity of DCT is quite high as it involves with floating point operations. Hence a family of orthogonal transforms called dyadic transform with the principle of dyadic symmetry [14] is reported for transform coding. In [15], Richardson reported a coding of residual macro block on (4x4) DCT with few changes like integer DCT, inverse DCT in accordance with H.264 standard [16] and a scaling multiplication embedded on quantization. Instead of DCT, Discrete Wavelet Transform is then employed as it provides space-frequency decomposition of image [17] and it is a part of compression standard JPEG 2000 [3]. In order to reduce running time and memory requirements, different strategies on wavelet transform [18-20] are also reported for image coding. But wavelet transform cannot be well suited to represent 2D singularities along edges and contours. Hence, regions of interest (ROI) coding on top of JPEG2000 has been introduced in [21]. As an alternative to DCT and Wavelets, Orthogonal polynomials transformation which is utilised as a model to represent low level features [22, 23] is introduced in [24, 25]. Besides the choice of transformation, quantization and entropy encoding are the other two important steps involved in any transform coding. In the case of quantization, scalar and vector quantization techniques on different transform coefficients are found to have use in transform coding techniques [26]. In the JPEG base line system [1], the quantized transform coefficients are reordered with Zig-Zag scanning so as to form a 1-Dimensional sequence of signals. The DC values are difference pulse code modulated and AC coefficients are Huffman coded with variable length code (VLC). There are also standard dictionary look-up tables separately for

coding DC and AC coefficients. The time consumed for this is higher and is directly proportional to the number of transform coefficients to be entropy coded. To reduce this, recently a low complexity approximation for discrete Tchebichef transform has been reported in [27] for image coding. Still reduction of transform coefficients that takes less time to refer the dictionary look-up table is essential and the same is achieved in the work proposed in this paper, on the transform coefficients obtained with orthogonal polynomials and lifting scheme [28, 29].
This paper is organised as follows: Section 2 overviews the orthogonal polynomials transform with any size of the point spread operator. Section 3 describes the lifting scheme to be applied with orthogonal polynomials transform coefficients so as to give birth to transcoded coefficients. Section 4 describes the quantization scheme and entropy coding. In section 5 performance measures are given. Experiments and results are presented in section 6 and conclusion is drawn in section 7.

II. Orthogonal Polynomials Transformation

In this section the orthogonal polynomials model for analyzing the 2-D monochrome image is revisited. In order to design a transform coding a linear 2-D image formation system is considered around a Cartesian coordinate separable blurring point spread operator in which the image I results in the superposition of the point source of impulse weighted by the value of the object f . Expressing the object function f in terms of derivatives of the image function I relative to its Cartesian coordinates is very useful for analyzing the image. The point spread function $M\left(x, y\right)$ can be considered to be real valued function defined for $\left(x, y\right)\in X\times Y,$ where X and Y are ordered subsets of real values. In case of gray-level image of size $\left(n\times m\right)$ where $X\left(rows\right)$ consists of a finite set which for convenience can be labeled as $\left\{0, 1, \ldots, n-1\right\}$ the function $M\left(x, y\right)$ reduces to a sequence of functions.

$$M\left(i, t\right)=u_i(t), i, t=0, 1, \ldots, n-1 \qquad (1)$$

The linear two dimensional transformations can be defined by the point spread operator $M\left(x, y\right)\left(M\left(i, t\right)=u_i\left(t\right)\right)$ as shown in equation (2.2).

$$\beta'\left(\zeta, \eta\right)=\int_{x\in X}\int_{y\in Y} M\left(\zeta, x\right) M\left(\eta, y\right) I\left(x, y\right) dxdy \qquad (2)$$

Considering both *X* and *Y* to be a finite set of values $\left\{0, 1, 2, \ldots, n-1\right\}$ equation (2) can be written in matrix notation as follows

$$\left|\beta'_{ij}\right|=\left(\left|M\right|\otimes\left|M\right|\right)^t\left|I\right| \qquad (3)$$

Where $\otimes$ is the outer product $\left|\beta'_{ij}\right|$ are n^2 matrices arranged in the dictionary sequence I is the image $\left|\beta'_{ij}\right|$ are the coefficients of transformation and $\left|M\right|$ is

$$|M|=\begin{vmatrix} u_0(t_0)\ u_1(t_0)\cdots u_{n-1}(t_0) \\ u_0(t_1)\ u_1(t_1)\cdots u_{n-1}(t_1) \\ \vdots \\ u_0(t_{n-1})\ u_1(t_{n-1})\cdots u_{n-1}(t_{n-1}) \end{vmatrix} \qquad (4)$$

The set of orthogonal polynomials $u_0\left(t\right),\ u_1\left(t\right), \ldots, u_{n-1}\left(t\right)$ of degrees $\left\{0, 1, 2, \ldots, n-1\right\}$ respectively are considered. The generating formula for the polynomials is as follows

$u_{i+1}(t) = (t - \mu)u_i(t) - b_i(n)u_{i-1}(t)$ for $i \geq 1$ (5)

$u_1(t) = t - \mu$ and $u_0(t) = 1$

where

$$b_i(n)=\frac{\langle u_i, u_i\rangle}{\langle u_{i-1}, u_{i-1}\rangle}=\frac{\sum_{t=1}^{n} u_i^2(t)}{\sum_{t=1}^{n} u_{i-1}^2(t)}$$

And $\mu=\frac{1}{n}\sum_{t=1}^{n} t$

Considering the range of values of t to be $t_i = i \quad i = 1 \; 2 \; 3 \; \ldots \; n$ we get

$$b_i(n) = \frac{i^2(n^2 - i^2)}{4(4i^2 - 1)},$$

$$\mu = \frac{1}{n}\sum_{t=1}^{n} t = \frac{n+1}{2}$$

Next point spread operator $|M|$ of different sizes are constructed from the above orthogonal polynomials as follows

$$|M| = \begin{vmatrix} u_0(t_0)\; u_1(t_0) \cdots u_{n-1}(t_0) \\ u_0(t_1)\; u_1(t_1) \cdots u_{n-1}(t_1) \\ \vdots \\ u_0(t_{n-1})\; u_1(t_{n-1}) \cdots u_{n-1}(t_{n-1}) \end{vmatrix} \qquad (6)$$

for $n \geq 2$ and $t_i = i$.

For convenience of point spread operations the elements of $|M|$ are scaled to make them integers.

The point spread operator in equation (4) that defines the linear orthogonal transformation for image analysis can be obtained as $|M| \otimes |M|$ where $|M|$ can be computed and scaled from equation (5) as follows.

$$|M| = \begin{vmatrix} u_0(t_0)\; u_1(t_0)\; u_2(t_0) \\ u_0(t_1)\; u_1(t_1)\; u_2(t_1) \\ u_0(t_2)\; u_1(t_2)\; u_2(t_2) \end{vmatrix} = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix} \qquad (7)$$

For the purpose of image reconstruction, the set of nine two dimensional basis operators O_{ij}^{n} ($0 \leq i \;\; j \leq n$-1) can be computed as

$O_{ij}^{n} = \hat{u}_i \otimes \hat{u}_j^{t}$ (8)

where $\hat{u}_i$ is the $(i + 1)^{st}$ column vector of $|M|$.

For example polynomials basis operators of size (3 x 3) are

$$\left[O_{00}^{3}\right] = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad \left[O_{01}^{3}\right] = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad \left[O_{02}^{3}\right] = \begin{bmatrix} 1 & -2 & 1 \\ 1 & -2 & 1 \\ 1 & -2 & 1 \end{bmatrix}$$

$$\left[O_{10}^{3}\right] = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \qquad \left[O_{11}^{3}\right] = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix} \qquad \left[O_{12}^{3}\right] = \begin{bmatrix} -1 & 2 & -1 \\ 0 & 0 & 0 \\ 1 & -2 & 1 \end{bmatrix}$$

$$\left[O_{20}^{3}\right] = \begin{bmatrix} 1 & 1 & 1 \\ -2 & -2 & -2 \\ 1 & 0 & 1 \end{bmatrix} \qquad \left[O_{21}^{3}\right] = \begin{bmatrix} -1 & 0 & 1 \\ 2 & 0 & -2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \left[O_{22}^{3}\right] = \begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix}$$

In this proposed transform coding scheme, we employ (8x8) window and hence the (8x8) operator for orthogonal polynomials model is given below

$$\begin{pmatrix} 1 & -7 & 7 & -7 & 7 & -7 & 1 & -1 \\ 1 & -5 & 1 & 5 & -13 & 23 & -5 & 7 \\ 1 & -3 & -3 & 7 & -3 & -17 & 9 & -21 \\ 1 & -1 & -5 & 3 & 9 & -15 & -5 & -35 \\ 1 & 1 & -5 & -3 & 9 & 15 & -5 & -35 \\ 1 & 3 & -3 & -7 & -3 & 17 & 9 & 21 \\ 1 & 5 & 1 & -5 & -13 & -23 & -5 & -7 \\ 1 & 7 & 7 & 7 & 7 & 7 & 1 & 1 \end{pmatrix}$$

It is proved in [25] that the proposed transformation is complete and hence the transformed image can be reconstructed perfectly. Also more details about this model can be found in [24.25].

III. Lifting Scheme

The transform coefficients obtained after applying the orthogonal polynomials transform as described in the previous section shall be subjected to lifting scheme as described below.

In this proposed technique each orthogonal polynomials transform coefficient is going to be factored into one or more lifting stages as reported in [29]. The lifting stage has 4 steps: Split, Predict, Update and Normalize.

Split: The given OPT coefficient signal X[n] is first split into even and odd subsets represented as $X_e[\mathrm{n}]$ and $X_o[\mathrm{n}]$

where $X_e[\mathrm{n}] = X[2\mathrm{n}]$ and $X_o[\mathrm{n}] = X[2\mathrm{n}+1]$ (13)

Predict: $X_o[\mathrm{n}]$ is then predicated from neighbouring even subsets $X_e[\mathrm{n}]$. This predictor p(.) is a linear combination of neighbouring even subsets

$$p(\mathrm{X}_e)[\mathrm{n}] = \sum_i p_i X_e[\mathrm{n+i}] \quad (14)$$

Here pi is the predication high pass filter coefficients. From this d[n], the detail coefficients are obtained as

$$d[\mathrm{n}] = X_o[\mathrm{n}] - p(\mathrm{X}_e)[\mathrm{n}] \quad (15)$$

In order to obtain odd subsets $X_o[\mathrm{n}]$, we use the even subset $X_e[\mathrm{n}]$ and predication residual $d[\mathrm{n}]$. That is

$$X_o[\mathrm{n}] = d[\mathrm{n}] + p(\mathrm{X}_e)[\mathrm{n}] \quad (16)$$

Update: This transforms the even subset $X_o[\mathrm{n}]$ into low-pass filter version of X[n]. It means that by updating the linear combination of predication residuals $d[\mathrm{n}]$ a coarse approximation is found out in terms of approximation coefficients C[n], which is obtained from the relation

$$\mathrm{C}[\mathrm{n}] = X_e[\mathrm{n}] + \mathrm{U(d)}[\mathrm{n}] \quad (17)$$

where $\mathrm{U(d)}[\mathrm{n}] = \sum_j u_j d[\mathrm{n+j}]$. Here u_j is the low pass filter coefficient. It can be noted that

$$X_e[\mathrm{n}] = C[\mathrm{n}] + \mathrm{U(d)}[\mathrm{n}] \quad (18)$$

Normalize: In this step the outputs of lifting are weighted by ke and ko, used to normalize the energy of scaling and orthogonal polynomials transformation coefficients. In this work they are taken $\sqrt{1}$ and $\sqrt[1]{2}$ respectively.

In the case of 2-D signals we repeat the same for vertical transform coefficients. For inverse lifting we perform: Undo normalizes Undo update Undo predict and merge. At the same time, they can be easily recovered in the decoding part. Having described the transcoding part, the proposed coding then utilizes simple quantization scheme and the same is presented in the next section.

The process of applying lifting scheme on orthogonal polynomials transform coding yields reduced number of orthogonal polynomials transcoded coefficients. For example, if the image block under consideration is of size (nxn), then the transcoded coefficients shall have a block of size (nxn/2). Hence the proposed transcoding scheme shall take less time, as only 50% of the coefficients are effectively removed for further processing.

IV. Quantization And Entropy Coding

In this Section we present the quantization and entropy coding on the orthogonal polynomials transform coefficients for the purpose of effective storage which can give better compression ratio. The quantization process reduces the number of bits needed to store the transformed coefficient values by reducing the precision. The quantization is implemented using a quantization matrix, whose formula, as in JPEG given below.

Quantized value (i, j) =round[(OPT(i,j)) / Quantum(i,j)]

where [OPT(i,j)] is the transcoded coefficient matrix obtained using the proposed orthogonal polynomials transformation. The quantum value matrix is obtained through an integer, called quality factor. The quality factor which is an user input, is generally in the range of 0-25, and specifies the quantum value, for every element position in the original polynomials transform coefficient matrix. The quality factor is chosen in such a way that it can discard higher frequency coefficients elegantly. That is when the quality factor is high, the

quantum value corresponding to the higher frequency coefficient sample positions shall be high so that corresponding quantized value (i,j) can be zero. Thus the quantum value indicates what the step size is going to be for an element in the compressed rendition of the picture, with the values ranging from 1 to 255.
The quantized transform coefficients are then subjected to entropy coding using variable length coding (VLC).Since the amount of information conveyed by each transcoded coefficient is different , it is desired to assign varying number of bits to the different transform coefficients. The transcoded coefficients are first reordered using zig-zag scanning to form 1-D sequence. In the case of JPEG standard, AC and DC coefficients are entropy coded with Huffman coding and variable length coding separately, as a dictionary look up table. This requires n square look-up time for each transform coefficient of the block of size (nxn). But in this work as we have nxn/2 orthogonal polynomials transcoded coefficients, it is obvious that the proposed entropy coding takes only 50% of original coding scheme. This greatly saves computation time required for entropy coding, and hence both in the encoder and decoder parts of the proposed orthogonal polynomials transcoded scheme. Standard VLC tables specified in the JPEG baseline system are employed in this entropy coding part.

Since the Huffman coded binary sequence is instantaneous and uniquely decodable, the compressed sub image can be decompressed easily in a simple lookup table manner. The regenerated array of transcoded coefficients is reordered into a two dimensional block from the 1-D regenerated zig-zag sequence and also subjected to inverse lifting scheme. We then reconstruct the sub image under analysis by using the proposed polynomials basis operators, defined in the section 2. Any difference between the original and the reconstructed sub image as a result of lossy nature of the proposed transform coding and decoding process is evaluated as in the next section.

V. Performance Measure

In order to evaluate the performance of the proposed image compression scheme, it is necessary to define a measurement that can estimate the difference between the original image and the reconstructed image. Two common measurements that are used to measure are the compression are the Mean square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). They are described below:

$$PSNR = 10\log_{10}\left(\frac{255}{e_{mse}^2}\right)^2 \qquad (19)$$

where the average mean square error e_{mse}^2

$$e_{mse}^2 = \frac{1}{NM}\sum_{i=0}^{N}\sum_{j=0}^{M} E\left[R(i,j) - R^{'}(i,j)\right]^2 \qquad (20)$$

Here $R(i,j)$ is the (N x M) input image and $R^{'}(i,j)$ is the (N x M) reconstructed image.

VI. Experiments And Results

The proposed image compression scheme with orthogonal polynomials transcoded coefficients is experimented with more than 200 images, which include natural images and images from open source [30]. Two sample images, namely Lena and Pepper images, which are of size (256x256) with pixel values in the range 0-255 are presented in figure-1.

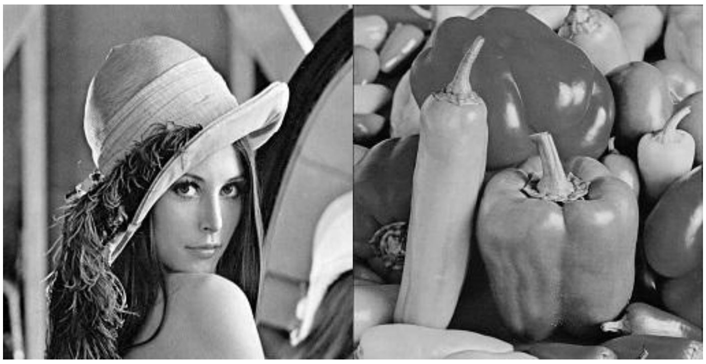

Figure 1: Original Images (a) Lena (b) Pepper

The input images are first partitioned into (8x8) blocks and orthogonal polynomials transformation is applied as described in section 2. The resulting transform coefficients are then subjected to lifting scheme as described in 3. This results in orthogonal polynomials transcoded coefficients which is only half of the original transform coefficients. These transform coefficients are then subjected to simple scalar quantization, with quality factor, as described in section 4. The resultant quantized coefficients are entropy coded with Huffman coding and variable length coding with standard JPEG look-up dictionary, giving bit streams of compressed images corresponding to the original images.

The experiment is repeated for different quality factors and the results are noted. The performance of the proposed compression scheme with orthogonal polynomials transcoded coefficients is measured in terms of PSNR and MSEas described in section 5.

For the lena image shown in figure 1(a), the proposed scheme gives PSNR and MSE values of 40.16 db and 6.25 respectively, when the quality factor is 10. For the same quality factor the pepper image shown in the figure 1(b), the proposed compression scheme gives 27.76 db and 108.87 respectively for PSNR and MSE. Similarly, when the quality factor is relaxed to 15, the proposed compression scheme gives a PSNR of 36.23 db and MSE of 15.45 for the lena image shown in the figure 1(a). For the pepper image , for a quality factor of 15, the proposed compression scheme gives a PSNR of 26.48 db and MSE of 146.06. These results along with, bit per pixel (BPP) measurement and compression ratio achieved with the proposed compression scheme is presented in table 1.

For the purpose of reconstruction, the reverse process is carried out. The result of decompressed images, corresponding to the original images shown in figure 1 with the proposed compression scheme is presented in figures 2.a and 3 when the quality factor in quantisation stage is 10 and 15 respectively.


Figure 2: Results of proposed compression scheme when the quality factor is 10.
(a) Lena (b) Pepper

(a) (b)

(a) (b)

Figure 2: Results of proposed transform coding schemes when quality factor is 15 (a) Lena (b) Pepper

Table1. Performance Measures obtained with the proposed compression scheme

S.NO	IMAGE	QUALITY FACTOR	TIME	PSNR	MSE	COMPRESSION RATIO	BPP
1	Lena	10	7363	40.16	6.25	0.97	0.21
2	Lena	15	7566	36.23	15.45	0.97	0.18
3	Pepper	10	10358	27.76	108.87	0.95	0.38
4	Pepper	15	10779	26.48	146.06	0.96	0.28

VII. Conclusion

In this paper, a simple compression scheme with orthogonal polynomials coefficients is presented. Initially, the input image is partitioned into blocks and applied with orthogonal polynomials transformation. In order to achieve fastness, a transcoding scheme with lifting is adopted, that converts to consumption of only 50% of the orthogonal polynomials transform coefficients. Then transcoded coefficients are subjected to scalar quantization and entropy coding as in JPEG system with reduced time consumption for dictionary look-up. The proposed scheme could achieve a compression ratio as high as 97.3% even for the quality factor of 10.

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