DOI: 10.21917/ijivp.2010.0005

TEXTURE PRESERVING IMAGE CODING USING ORTHOGONAL POLYNOMIALS

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Abstract
In order to replace the artifacts in the textured background, a new texture preserving image coder using the set of orthogonal polynomials is proposed in this paper. The proposed scheme is based on the model that represents textures using points spread operator relating to a linear system. In the proposed texture based image coding scheme, the encoder first identifies textured regions, which are then analyzed to produce the model features. Then these features are later transmitted to decoder which decodes to form a synthetic texture and results into synthetic stage. The proposed modeling delivers to attain high compression ratio by maintaining constantly excellent visual quality. 92.31% with a PSNR value of 31.93dB when the quality factor is 5 for D96 image is achieved by the proposed scheme. By keeping up the quality factor as a constant constrained, we obtain 91.11% of compression ratio with a PSNR value of 33.26dB for different set of image that is, D38 image.

Keywords:
Texture Preserving Image Coder, Points Spread Operator, Synthetic Texture, Texture Modeling and Compression Ratio

1. INTRODUCTION

Texture may be defined in terms structure, which literally composed of a ample number of more or less ordered, similar elements or patterns. The primitives and their placement rules can characterize observable texture. If the primitives have gray level variation within a small image region it is known as micro texture. Textured image more often crop up in natural scene or from abraded, torn or worn surfaces of many objects, so this strive path to Micro texture. One of challenging problem in computer vision can be discarded by Texture analysis; this might be best solution for everlasting problems in computer vision. Texture identification, texture classification, texture segmentation texture synthesis and shape from texture are the main problems faced in texture analysis. Textures contain repeating patterns and high frequency information that are not well compressed by transform coding technique. Compressed images are impaired by various types of artifacts such as blocking, blur, ringing etc.

In this work, an image region is represented as a linear combination of responses of the proposed difference operators, developed from the set of orthogonal polynomials. Based on the effect of this operator, micro textures have been identified and then represented as a decimal number. Once the texture is represented in the polynomial domain, the properties of texture can be captured relatively easily and therefore modeled efficiently. The orthogonal effects due to the spatial variations and their corresponding variances are computed, for texture representation and for subsequent texture preserving image coding.

Over the years, numerous methods have been proposed for the texture analysis. These methods are broadly divided into four categories, namely, statistical methods [1], structural methods [2], model based methods [3] and filter based (or) signal processing methods [4]. Filter based methods can be grouped again into three categories (i) spatial domain filtering [5] (ii) frequency domain filtering [6] and (iii) spatial frequency domain filtering [7]. Other works include Wigner distribution [8], Gabor filter [9], wavelet transformation [10, 11]. Due to the unceasing demand for a larger compression ratio with satisfactory image quality, texture modeling has gained increased interest from researchers in the field of image compression [12, 13]. Ryan et al. [14] proposes an image coding scheme where the input image is segmented into texture and non-texture regions and operated directly in the wavelet domain and model the texture by an auto-regressive model. Debure and Kubota [15] proposed a scheme for texture compression based on wavelet transform and the auto regressive texture model. This scheme investigates the influences of the initial condition and the order of an Auto Regressive model on the resulting texture model. Recently, Nadenau et al. [16] proposed a hybrid scheme that encodes the structural image information by conventional wavelet codec and the stochastic texture in model-based manner. In [17, 18], the advantages and disadvantages of texture analysis and synthesis methods are presented.

Motivated by these considerations a new texture analysis and synthesis algorithm is proposed for image compression in this paper. The proposed scheme is based on model that represents textures using points spread operator relating to a linear system. The objective of this work is to clearly rebuild the missing texture during the decompression-decoding process by texture synthesis method from the extracted texture in the compression encoding process. Section-II presents an image region is represented as a linear combination of the responses of the proposed texture model in the presence of additive white Gaussian noise and the texture regions are extracted with texture analysis scheme and represent the texture with decimal number are discussed in section-III. In section-IV, the image is compressed with quantization and entropy coding. Experiments results and Comparison with other methods are presented in section-V. Finally, section-VI gives the conclusion.

2. PROPOSED MODEL FOR TEXTURE CHARACTERIZATION

The proposed model for texture characterization is based on the statistical design of experiment approach. We consider an (n x n) image region from the image I (x, y), where x and y are two spatial coordinates, as follows

$$I(x, y) = g(x, y) + \acute{\eta}(x, y) \quad (1)$$

In equation (1), g(x, y) accounts for the spatial variation owing to texture and ή(x, y) is the spatial variation owing to additive noise. In order to measure the spatial variations owing to texture and noise separately, we represent I(x, y), as shown in equation (2), that follows in terms of a set of uncorrelated basis spatial variations.

$$I_{i,j}^{n} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \beta_{ij} \left[O_{i,j}^{n}\right] \quad (2)$$

where, $[I^n_{i,j}]$ is the (n x n) gray level image matrix, $[O^n_{i,j}]$ accounts for the spatial model variation and β_{ij} is the (i,j) coefficient of variation. β_{ij} is basically the effect of the variation accounted for by $[O^n_{i,j}]$ over the image region I(x,y). We select $[O^n_{i,j}]$'s in such a manner that the effects . β_{ij}'s are orthogonal to each other. Using the statistical design of experiments paradigm, we consider I(x, y) to be the yields of the experiments with two factors x and y, each at n different levels. Two types of spatial variations are considered in this work. In one, one spatial coordinate varies at a time, when the other remains constant. In the other, both the spatial coordinates vary jointly. The orthogonal effects due to the former kind of variation are called the main effects, whereas, the orthogonal effects due to the latter kind of variation are called interaction effects. It has been observed experimentally that the spatial variation that causes the interaction effects are owing to micro texture present in the image region $[I^n_{i,j}]$. The other spatial variation are owing to noise present in the image region $[I^n_{i,j}]$. Hence, the texture is characterized by the interaction effects. This is because, in presence of micro texture the two factors x and y do not operate independently rather the effect of one is dependent on different levels of the other. For computing orthogonal effects, the set of orthogonal polynominals, which have been presented in [19], has been used. $[O^n_{i,j}]$ in equation 2 are (n x n) polynominal basis operators and β_{ij}'s are orthogonal effects due to spatial variations of gray levels present in the image region $[I^n_{i,j}]$. The spatial variations are modeled by the polynomial basis operators $[O^n_{i,j}]$'s. The complete set of basis operators of sizes (2 x 2) and (3 x 3) are given below.

The polynomial basis operators of size (2 x 2) are:

$$\left[O_{00}^{2}\right] = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, \quad \left[O_{01}^{2}\right] = \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix},$$

$$\left[O_{10}^{2}\right] = \begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix}, \quad \left[O_{11}^{2}\right] = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

where $|M| = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$

The polynomial basis operators of size (3 x 3) are:

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

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

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

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

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

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

We also show that a set of (n x n) (n ≥ 2) polynomial operators forms a basis, i.e. it is complete and linearly independent.

3. TEXTURE REPRESENTATION

From grouping criteria for textures, we model the texture as the responses of the operators $[O^n_{i,j}]$'s. The responses of the remaining operators are considered to the responses towards noise presented in a textured image. Now we present a scheme to represent the detected textures properly by local descriptors. The local descriptor for the micro texture is computed. The identified micro textured regions are required to be represented properly so that it can be used for texture model. A (3 x 3) image region is considered as a sample for performing the test. The mean square error variance (msv) can be computed as follows

$$msv = \frac{\sum Z_{ij}^{2}}{\|V\|} \quad (3)$$

where $\|v\|$ is the cardinality of the set V. Each of the variances in {A+B-V} is divided by the mean square error variance (*msv*) for computing the signal-to-noise ratio, where A is the set of coefficients contributing towards texture, B accounts for noise and V is the subset of A that account for error within texture coefficients. In case of significant contribution, the pixel in the original textured image whose zonal position corresponds to the zonal position of the variance term corresponding to the interaction effect is represented as 1; otherwise, it is represented as 0. The positions corresponding to the variance terms in V which are used for computing msv are presented as 0s. So there is a mapping from the gray level image into a string of binary digits 0 and 1 as follows:

$$\begin{bmatrix} i_1 & i_2 & i_3 \\ i_4 & i_5 & i_6 \\ i_7 & i_8 & i_9 \end{bmatrix} \Rightarrow \begin{bmatrix} p_0 & p_1 & p_2 \\ p_3 & p_4 & p_5 \\ p_6 & p_7 & p_8 \end{bmatrix}$$

Gray level image Texture representation

where pn = {0, 1} and n = 1, 2, …, 8 Now, the encrypted local description of micro texture is quantified as a decimal number called pronum. pronum is computed as

$$Pronum = \sum_{n-1}^{8} P_n \times 2^{n-1} \quad (4)$$

The central pixel i_5 of the image under analysis corresponds to this pronum. Subsequent regions in the image are also considered for computing pronums by sliding a window of size (3 x 3) in the raster scan fashion. The number of occurrences of these pronums is called prospectrum. A prospectrum of an image describes the texture present in the image globally. Since the pronum ranges from 0 to 255 there may be totally 256 components in a prospectrum and reflects the histogram of pronums.

4. QUANTIZATION AND BIT ALLOCATION

In this section, a quantization of orthogonal polynomials transform coefficients is proposed so as to achieve higher compression ratio. The quantization is implemented using a quantization matrix, whose formula, as in JPEG [20] is given below:

$$\textit{Quantized value } (i, j) = \textit{round}\left[\frac{OPT\,(i,\ j)}{Quantum\,(i,\ j)}\right] \qquad (5)$$

where transform co-efficient matrix, *OPT(i,j)* is obtained by means of proposed orthogonal polynomials transformation. By using quality factor, quantum value matrix *Qunatum(i,j)* is obtained via an integer. Basically quality factor, user input value ranges from 0 – 25 and this is mainly for identifying the quantum value, for every element position in the original polynomials transform coefficient matrix.

The quantized transform coefficients are subjected to bit allocation scheme using variable length coding. This coding scheme combines three different steps. The first step changes the DC values. For this purpose the quantized transform coefficients are re-ordered in zigzag sequence to form a 1-D sequence. Due to the fact that DC coefficients of the proposed orthogonal polynomials based coding have high magnitude and the DC values of neighboring blocks are not differing substantially, the DC values are subjected to difference pulse code modulation (DPCM). The first and foremost element of the zigzag sequence represents the difference pulse code modulated DC value and among the remaining AC coefficients, the non-zero AC coefficients are Huffman coded using variable length code (VLC) that defines the value of the coefficient and the number of preceding zeros.JPEG baseline system is used for this purpose, which come under the category of Standard VLC tables.

Any difference between the original and reconstructed sub image as a result of lossy nature of the proposed transform coding and decoding process is evaluated. The performance of the proposed texture preserving transform coding is reported by computing the peek-signal to noise ratio (PSNR), which is defined as

$$PSNR = 10\log_{10}\left[\frac{255}{e_{ms}^2}\right]^2 \qquad (6)$$

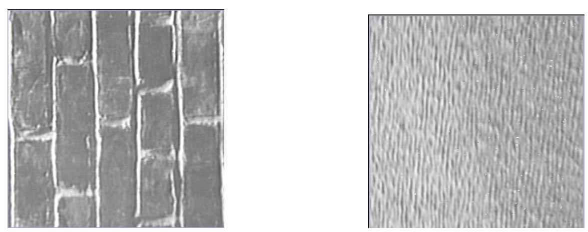
Where the average mean square error e_{ms}^2

$$e_{ms}^2 = \frac{1}{RC}\sum_{i=1}^{R}\sum_{i=1}^{C} E\left(I_{i,j} - I'_{i,j}\right)^2 \qquad (7)$$

where $\{I_{i,j}\}$ and $\{I'_{i,j}\}$represents the (R x C) original and reproduced images respectively.

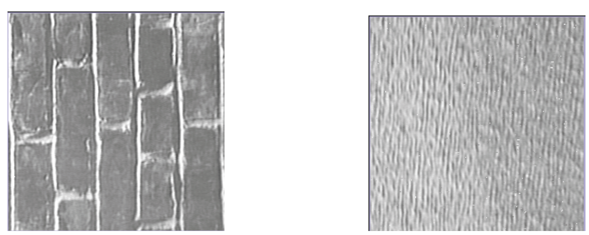
5. EXPERIMENTS AND RESULTS

The proposed orthogonal polynomials based texture preserving compression has been experimented with various test images, having different textual primitives and here we present the results of two standard texture images. These original images namely D96 and D38 both of size (256 x 256) with pixel values in the range 0–255 are shown in Fig.1. The input images are partitioned into various non-overlapping sub-images of size (4 x 4), and are subjected to the proposed orthogonal polynomials based transformation to obtain the transform coefficients β'_{ij}. All these blocks containing $\beta'ij$ are then classified into texture block or non-texture block. If the block contains texture then the coefficients contributing towards textures are identified with pronum as described in section III. Let these coefficients be $\beta'_{t\,ij}$. A compression ratio of 89.31% with a PSNR value of 31.93dB is achieved when the quality factor is 5 for D96 image and for the same quality factor, a compression ratio of 86.11% with a PSNR value of 33.26dB is obtained for the D38 image and the results are shown in Fig.2.



(a) D96 (b) D38

Fig.1. Original texture images considered for texture preserving transform coding



(a) D96 (b) D38

Fig.2. Results of the proposed scheme when Quality Factor is 5

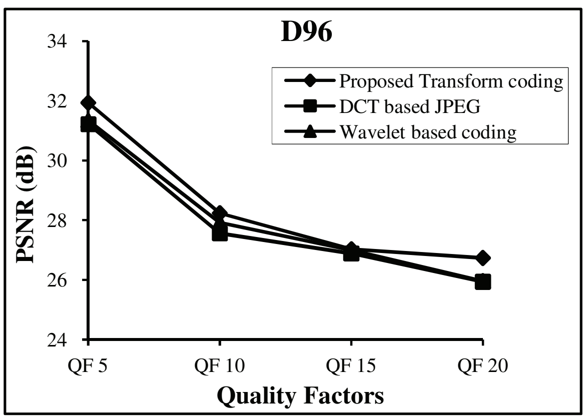
The proposed texture preserving transform coding is compared with the DCT based JPEG. Here, the transform coefficients obtained after the proposed transformation with different quality factors and the bit allocated using variable length code. For the D38 image with quality factor of 5, the DCT based scheme gives a compression of 88% with PSNR value of 31.22 is obtained. With regard to D96 image, a compression of 88.42% with PSNR value of 31.34 is achieved when the quality factor of 5.

For the quality factor of 5, on the same D38 image, the wavelet-based scheme gives a compression of 86% with a PSNR 32.76 dB is resulted. For the quality factor of 5, on the same

D96 image, the wavelet-based scheme gives a compression of 85.11% with a PSNR 32.53 dB is resulted. The experiment is repeated for the quality factors 10, 15 and 20 and corresponding results are tabulated in the table 1. It is evident from the table 1 that the proposed texture preserving transform coding is giving better compression ratio than the DCT and wavelet based coding results and their corresponding PSNR values against different quality factor of texture based transform coding are plotted on the graph for D96 and D38 images are presented in Fig.3.

Table.1. Compression Ratio (CR) and PSNR values obtained by proposed scheme, DCT and Wavelet based scheme

Image	Q.F.	Proposed Transform coding		DCT based JPEG		Wavelet based coding	
		CR (%)	PSNR (dB)	CR (%)	PSNR (dB)	CR (%)	PSNR (dB)
D96	5	89.11	31.93	88.00	31.22	88.42	31.34
	10	91.33	28.23	90.42	27.56	90.87	27.92
	15	93.24	27.02	92.56	26.88	92.63	26.99
	20	93.92	26.73	92.61	25.93	92.89	25.95
D38	5	86.11	32.76	85.01	31.98	85.11	32.53
	10	90.53	29.11	89.55	28.89	89.23	28.92
	15	91.31	26.86	90.11	26.14	89.91	26.53
	20	92.51	25.12	91.23	24.32	91.34	24.48



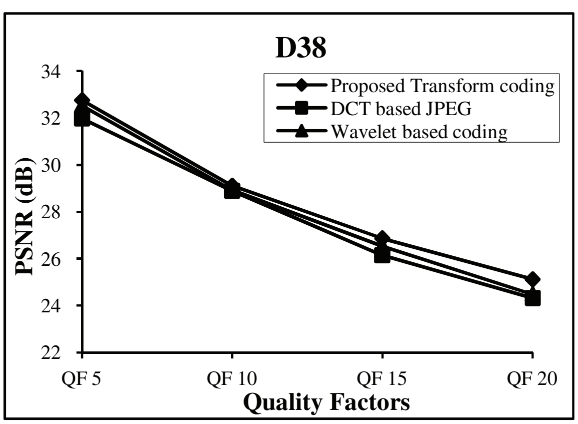


Fig.3. Compression results by the proposed coding, DCT based JPEG and Wavelet based scheme

6. CONCLUSION

A new texture preserving image coder using orthogonal polynomial has been presented in this paper. The proposed scheme is based on the model that represents textures using point spread operator relating to linear system. The encoder first identifies textured regions, and these regions are analyzed to produce the model features. These features are transmitted to the decoder that produces a high quality texture based on these features through the synthesis stage. The proposed texture preserving method is used to remove the undesirable artifacts in image obtained after compression-decompression process.

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