Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 4, Issue. 8, August 2015, pg.91 – 97

RESEARCH ARTICLE

Image Compression based on Non-Linear Polynomial Prediction Model

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Abstract

This paper introduced a new image compression techniques based on using the modelling concept of polynomial second order Taylor series representation of nonlinear base. The results showed highly performance in terms of compression ratio and quality even with more complexity of coefficients estimation.

1. Introduction

Compression is the hart of multimedia subject, that control the amount of information saved and/or sends, implicitly affected computers and/or communication to reduce storage costs and/or transfer rate respectively.

A compression system generally, achieved by reducing the size of information required by exploited the redundancy. Image compression based on utilizing the redundancy within the image itself (i.e., image's structure or features) – referred to as statistical redundancy, along with the utilization of the limitations of human vision or perception – referred to as psycho-visual redundancy. Hence, lossless and lossy techniques available. In other words, lossless also called information preserving or error free techniques based on exploiting the statistical redundancy alone, in which the image compressed without losing information with low compression performance, basically based on rearrange or reorder the image content. On the other hand, lossy based on exploiting the psycho-visual redundancy, either solely or combined with statistical redundancy, in which remove content from the image, that degrades the compressed image quality with high compression performance. Reviews of lossless and lossy techniques can be found in [1-8].

The prediction coding techniques based on modelling concept increasingly used in image compression, due to simplicity, symmetry of encoder/decoder and flexibility of use are the most significant advantages of this technique [9]. The core of prediction coding lies in the design of mathematical models, in which predicting or estimating each pixel value from nearby or neighbouring pixels, and then followed by finding the differences between the predicted value and the actual value that called residual or prediction error [10-12].

Today, the polynomial linear based adopted by [13], and followed by [14-18] to compress the images effectively based on modelling distance between image pixels and the centre, using the linearization base or the first order Taylor series.

In this paper an extended approximated non-linear polynomial model (second order Taylor series) for compressing images utilized. The rest of the paper organized as follows, section 2 contains comprehensive clarification of the proposed system; the results of the proposed system, is given in section 3.

2. The Proposed System

The main taken concerns in the proposed system are:

- It shows the effectiveness of the extended the approximated polynomial model of nonlinear based of second order Taylor series form to compress images compared to the approximated polynomial model of linear based.
- It describes a fully compression system that takes advantage of spatial redundancy (i.e., correlation) that modelled using six coefficients (a_0,a_1,a_2,a_3,a_4,a_5) compared to the linear model of three coefficients (a_0,a_1,a_2)base. Along with eliminating unnecessary and unnoticeable redundancy (i.e., coding & psychovisual).

The steps below illustrate clearly the implementation of proposed system in details, the system layout shown in Figure (1):

Step 1: Load the original uncompressed gray image *G* of *BMP* format of size *N*×*N*.

Step 2: Partition the image *G* into nonoverlapping square fixed block of size *n*×*n*, then compute the estimated coefficients of the extended nonlinear model according to equations below, by first finding the a_1, a_2 and a_5 coefficients, such as:

$$a_1 = \frac{\sum_{x=0}^{n-1}\sum_{y=0}^{n-1} G(x,y)(x-xc)}{\sum_{x=0}^{n-1}\sum_{y=0}^{n-1}(x-xc)^2} \quad \ldots\ldots\ldots(1)$$

$$a_2 = \frac{\sum_{x=0}^{n-1}\sum_{y=0}^{n-1} G(x,y)(y-yc)}{\sum_{x=0}^{n-1}\sum_{y=0}^{n-1}(y-yc)^2} \quad \ldots\ldots\ldots(2)$$

$$a_5 = \frac{\sum_{x=0}^{n-1}\sum_{y=0}^{n-1} G(x,y)(x-xc)(y-yc)}{\sum_{x=0}^{n-1}\sum_{y=0}^{n-1}(x-xc)^2(y-yc)^2} \quad \ldots\ldots\ldots(3)$$

$$xc = yc = \frac{n-1}{2} \quad \ldots\ldots\ldots(4)$$

Where *xc* equal to *yc* that represents a block centre of size (*n*×*n*).

For the coefficients a_0,a_3 and a_4, the extended approximation polynomial mode can be summarized as:

$$V_1 = a_0W_1 + a_3W_2 + a_4W_2 \quad \ldots\ldots\ldots(5)$$

$$V_2 = a_0W_2 + a_3W_3 + a_4W_4 \quad \ldots\ldots\ldots(6)$$

$$V_3 = a_0W_2 + a_3W_4 + a_4W_3 \quad \ldots\ldots\ldots(7)$$

$$W_1 = n \times n \quad \ldots\ldots\ldots(8)$$

$$W_2 = \sum_{x=0}^{n-1}(x-xc)^2 = \sum_{y=0}^{n-1}(y-yc)^2 \quad \ldots\ldots\ldots(9)$$

$$W_3 = \sum_{x=0}^{n-1}(x-xc)^4 = \sum_{y=0}^{n-1}(y-yc)^4 \quad \ldots\ldots\ldots(10)$$

$$W_4 = \sum_{x=0}^{n-1}\sum_{y=0}^{n-1}(x-xc)^2(y-yc)^2 \quad \ldots\ldots\ldots(11)$$

Where

$$V_1 = \sum_{x=0}^{n-1}\sum_{y=0}^{n-1} G(x,y) \quad \ldots\ldots\ldots(12)$$

$$V_2 = \sum_{x=0}^{n-1}\sum_{y=0}^{n-1}(x-xc)^2 G(x,y) \quad \ldots\ldots\ldots(13)$$

$$V_3 = \sum_{x=0}^{n-1}\sum_{y=0}^{n-1}(y-yc)^2 G(x,y) \quad \ldots\ldots\ldots(14)$$

In order to find the required coefficients, apply the Crammers rule, where:

$$a_0 = \frac{\begin{vmatrix} V_1 & W_2 & W_2 \\ V_2 & W_3 & W_4 \\ V_3 & W_4 & W_3 \end{vmatrix}}{\begin{vmatrix} W_1 & W_2 & W_2 \\ W_2 & W_3 & W_4 \\ W_2 & W_4 & W_3 \end{vmatrix}} \quad \ldots\ldots\ldots(15)$$

$$a_3 = \frac{\begin{vmatrix} W_1 & V_1 & W_2 \\ W_2 & V_2 & W_4 \\ W_2 & V_3 & W_3 \end{vmatrix}}{\begin{vmatrix} W_1 & W_2 & W_2 \\ W_2 & W_3 & W_4 \\ W_2 & W_4 & W_3 \end{vmatrix}} \quad \ldots\ldots\ldots(16)$$

$$a_4 = \frac{\begin{vmatrix} W_1 & W_2 & V_1 \\ W_2 & W_3 & V_2 \\ W_2 & W_4 & V_3 \end{vmatrix}}{\begin{vmatrix} W_1 & W_2 & W_2 \\ W_2 & W_3 & W_4 \\ W_2 & W_4 & W_3 \end{vmatrix}} \quad \ldots\ldots\ldots(17)$$

Here in the nonlinear form, the polynomial representation approximation model required 6 coefficients to represents each block compared to the linear model that require 3 coefficients. Basically, the nonlinear based needs times two of linear model coefficients, in spite of that, the compression performance not affected by these additional coefficients since the residual decrease due to increase the modelling efficiency. The main reason of estimating the coefficients decorrelation or removing of interpixel (spatial) redundancy (interpixel) is possible, by using the modelling concept.

Step 3: Quantize the estimated coefficients from step above using the popular scalar uniform quantizer, simply by dividing the each of the computed coefficients by the quantization step to eliminate the psychovisual redundancy. Here 3 quantization level of values required according to coefficients importance, one for a_0 values, other one for the a_1 & a_2 and the last one for a_3,a_4 &a_5 values. The quantizer/dequantizer as shown in equations (18-23).

$$a0Q = round(\frac{a0}{QSa0}) \rightarrow a0D = a0Q \times QSa0 \text{.............(18)}$$

$$a1Q = round(\frac{a1}{QS_{a_1}}) \rightarrow a1D = a1Q \times QS_{a_1} \text{..........(19)} \quad a2Q = round(\frac{a2}{QS_{a_1}}) \rightarrow a2D = a2Q \times QS_{a_1} \text{........(20)}$$

$$a3Q = round(\frac{a3}{QS_{a_2}}) \rightarrow a3D = a3Q \times QS_{a_2} \text{........(21)} \quad a4Q = round(\frac{a4}{QS_{a_2}}) \rightarrow a4D = a4Q \times QS_{a_2} \text{........(22)}$$

$$a5Q = round(\frac{a5}{QS_{a_2}}) \rightarrow a5D = a5Q \times QS_{a_2} \text{........(23)}$$

Where QS_{a0} quantization step of a_0 coefficient, QS_{a_1} quantization step of a_1 & a_2 coefficients and QS_{a_2} quantization step of a_3, a_4 & a_5 coefficients.

Step 4: Create the predicted image $\tilde{G}$ as a nonlinear combination polynomial model of dequantized coefficients and pixel distance

$$\tilde{G} = a_0 W_1 + a_1(x - xc) + a_2(y - yc) + a_3(x - xc)^2 + a_4(y - yc)^2 + a_5(x - xc).(y - yc) \text{......(24)}$$

The predicted image $\tilde{G}$ corresponds to the modelled image representation that similar to the original image one, which is a weighted sum of coefficients and the pixel distance.

Step 5: Find the residual (prediction error) as a difference between original uncompressed image G and the predicted image $\tilde{G}$

$$\text{Re}\,s = G - \tilde{G} \text{..................................(25)}$$

The residual represents the information lost which can not be predicted accurately since the image features or characteristics cannot usually be fully described by a model where the details vary from part to part. The residual image acts as a quality indicator or measure of fit for the model, where a smaller residual indicates high compression gain, due to the adequate prediction model, while a larger residual indicates a low compression gain due to a poor prediction model [9].

Step 6: Quantize the residual image as in step 3 using the simple scalar uniform quantizer/dequantizer, such as:

$$\text{Re}\,sQ = round(\frac{\text{Re}\,s}{QS_{\text{Re}\,s}}) \rightarrow \text{Re}\,sQD = \text{Re}\,sQ \times QS_{\text{Re}\,s} \text{...........................(26)}$$

Where $QS_{\text{Re}\,s}$ quantization step of residual image.

Step 7: Encode the lossily quantized information of estimated coefficients and residual image using the LZW coding to eliminate/remove the coding redundancy by converting them into variable bit length coding.

The decoder reconstructs the compressed image $\hat{G}$ using only the information decoded of coefficients and residual, where the dequantized coefficients utilized to create the predicted image (see eq. 24), and then added to the dequantized residual image, such that:

$$\hat{G} = \tilde{G} + \text{Re}\,sQD \text{..(27)}$$

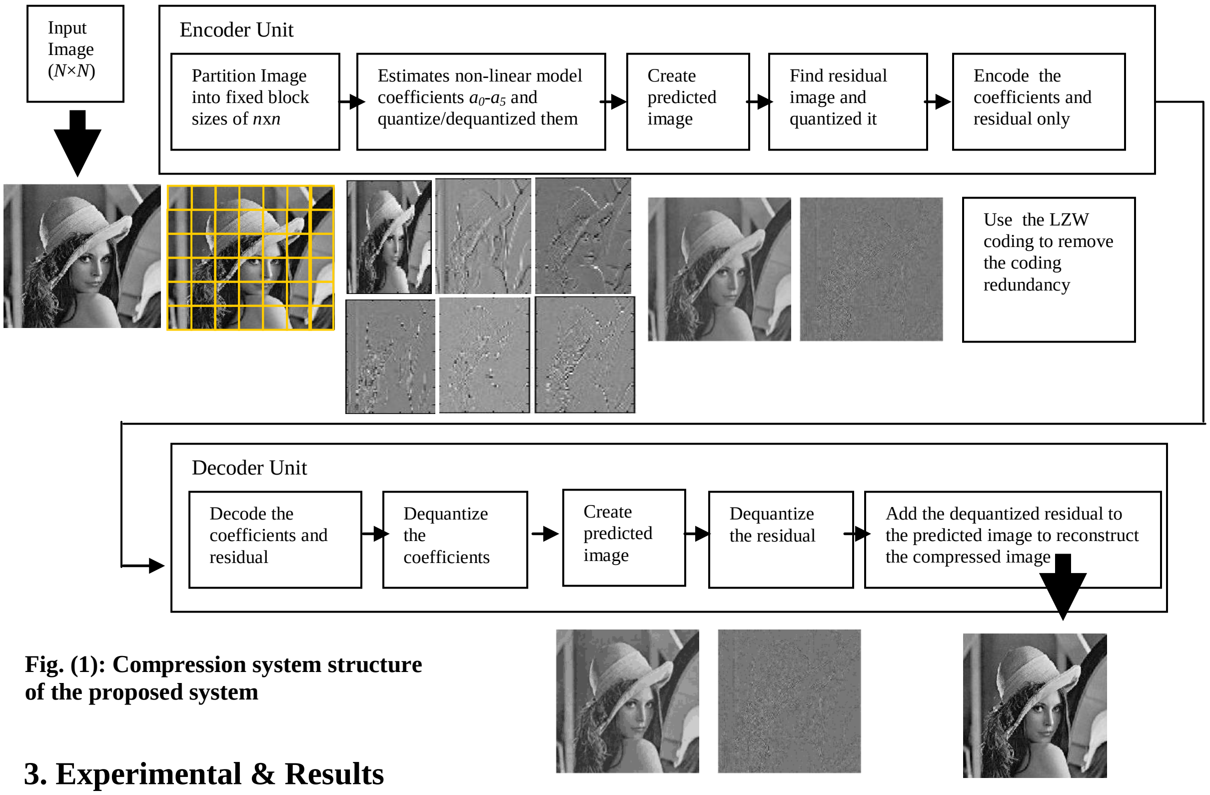


Fig. (1): Compression system structure of the proposed system

3. Experimental & Results

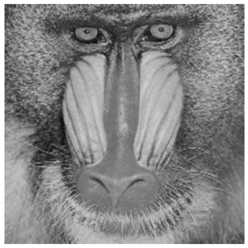
In general, as a lossy compression system utilized, the performance measure based on the objective fidelity criteria of Peak Signal to Noise Ratio (PSNR) (see equation 28), along with the Compression Ratio (CR) (see equation 29). Here various standard images were selected that characterized by variation in details, where the complex selected image of highly details such as Baboon (see figure 2a), the less complex one of medium details such as Lena (see figure 2b), and the simple image of small details such as Woman (see figure 2c), all the images are square gray scale images of size 256x256 pixels of 8 bit/per pixel.

$$PSNR = 10.\log_{10}\left[\frac{(255)^2}{\frac{1}{N\times N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\left[(\hat{I}(x,y)-I(x,y)\right]^2}\right] \quad \text{...............(28)}$$

$$CompressionRatio = \frac{SizeofOriginal\ Image}{SizeofCompressedInformation} \quad \text{................................(29)}$$

Table (1) illustrated the comparison performance of both linear and nonlinear polynomial coding techniques on the tested images, using two blocks of sizes 4×4 and 8×8, with quantization levels of coefficients of linear base equals to 1,3,3 and nonlinear base equals to 1,3,3,5,5,5, and with different quantization levels of residual image.

The results clearly showed the higher performance of nonlinear model base in terms of compression ratio and the quality that due to involving more coefficients of nonlinear terms where more accurately estimated the predicted image which leads to less residual error compared to the linear base model. Also the techniques of linear and nonlinear base implicitly affected by the block size and the quantization levels of the residual image, where for bigger block sizes and/or higher quantization levels higher compression achieved with lower PSNR quality image, and vice versa. Lastly, the results vary according to image details, where for the simple images more compression achieved compared to highly detailed image of low compression, since the techniques adopted of spatial domain base that directly affected by the image contents. Figure (3 a,b,c) showed the performance comparison between the linear and nonlinear base of the three tested images using block size of 4×4.

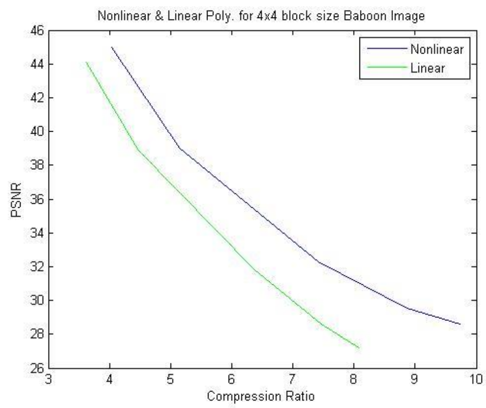


a

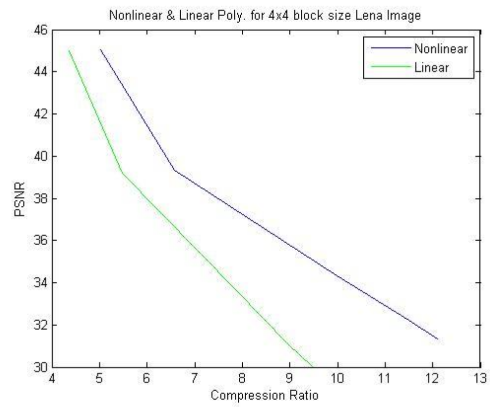
b

c

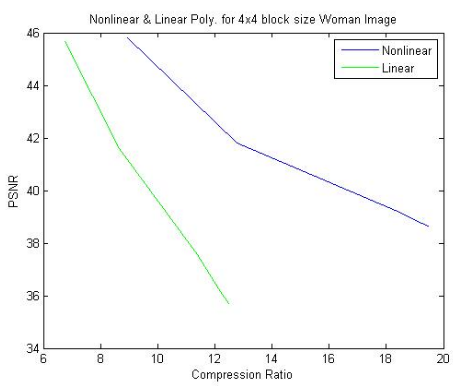
Fig(2): Tested images



a



b



c

Fig(3): Comparison performance between linear & nonlinear polynomial techniques of 4x4 block.

Table (1): Comparison performance between linear and non-linear polynomial coding techniques, using two blocks of sizes 4×4 and 8×8, with quantization levels of coefficients of linear base equals to 1,3,3 and nonlinear base equals to 1,3,3,5,5,5, and with different quantization levels of residual image.

Test Images	Quantization Residual	Non Linear Polynomial Coding				Linear Polynomial Coding			
		Block Size 4x4		Block Size 8x8		Block Size 4x4		Block Size 8x8	
		Quantization Coefficients 1,3,3,5,5,5				Quantization Coefficients 1,3,3			
		CR	PNR	CR	PNR	CR	PNR	CR	PNR
Baboon	**5**	4.0397	44.9740	4.3878	44.9681	3.6160	44.1215	4.2642	44.7611
	10	5.1417	39.0214	5.8405	38.9386	4.4725	38.8771	5.6134	38.9182
	25	7.4203	32.2936	9.4541	31.4740	6.3677	31.8107	9.0171	31.3333
	40	8.8706	29.5627	12.5668	28.0965	7.4608	28.5738	11.8253	27.8099
	50	9.7321	28.6181	14.5120	26.6307	8.0719	27.2236	13.5293	26.2638
Lena	**5**	5.0262	45.0210	5.4050	44.9575	4.3720	45.0033	5.1200	44.8753
	10	6.5859	39.3346	7.5044	39.0943	5.4805	39.1891	6.9831	39.0473
	25	9.9979	34.3206	12.8856	32.9040	7.8864	33.6292	11.6882	32.3062
	40	11.4935	32.2396	16.7826	30.1421	8.9481	31.1136	15.0277	29.3245
	50	12.1004	31.3507	18.9630	28.9324	9.4664	30.0078	16.8430	28.0343
Woman	**5**	8.9298	45.8173	8.9408	45.3904	6.7654	45.6704	7.8499	45.3391
	10	12.7726	41.8035	13.5601	40.5881	8.6459	41.5900	11.2162	40.1929
	25	18.3164	39.2463	23.9795	35.9456	11.3798	37.5748	18.7460	34.7760
	40	19.2583	38.7436	30.1454	34.1513	12.1950	36.1407	23.5656	32.3604
	50	19.4584	38.6397	32.7189	33.5085	12.4854	35.7176	26.1100	31.4090

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