Hierarchical Autoregressive for Image Compression

Ghadah Al-Khafaji
Baghdad University/Collage of Science/Computer Science Department
Hgkta2012@yahoo.com

Abstract

In this paper, a hierarchical autoregressive model (HAR) method is proposed for image compression. The suggested techniques, looks at improving the compression ratio along with preserving the image quality by involving a multi-layered modeling concept. In comparison with traditional predictive coding or autoregressive model on a series of tested images it shows that the suggested method is better than the traditional one.
Keywords: Image compression, autoregressive, hierarchal autoregressive
الكلمات المفتاحية : ضغط الصور، الانحدار الذاتي المترابط، الانحدار الذاتي المترابط الهرمي

المستخلص

يقدم هذا البحث طريقة الانحدار الذاتي الهرمي لضغط الصور. التقنية المقترحة تعمل على تحسين نسبة الضغط مع الحفاظ على جودة الصورة الناتجة من خلال ما ينطوي على مفهوم النمذجة متعددة الطبقات.اظهرت النتائج تفوق الطريقة المقترحة مقارنة مع نموذج الانحدار الذاتي التقليدية لسلسلة من الصور.

1. **Introduction**

Image compression techniques generally fall into two categories: lossless and lossy depending on the redundancy type exploited, where lossless is also called information preserving or error free techniques, in which the image is compressed without losing information as they rearrange or reorder the image content. Also they are based on the utilization of statistical redundancy alone (i.e., exploits coding redundancy and/or inter pixel redundancy) such as Huffman coding, arithmetic coding and Lempel-Ziv algorithm, while lossy removes content from the image, which degrades the compressed image quality. They are also based on the utilization of psycho-visual redundancy, either solely or combined with statistical redundancy such as vector quantization, fractal, wavelet and JPEG. Reviews of lossless and lossy techniques can be found in [1]-[6].
Today, there's an increase in roles of utilization predictive coding or Autoregressive (AR) for image compression [7]-[11]. Simplicity, symmetry of encoder and decoder and flexibility of use are the most significant advantages of this technique.
In this paper, a two-layer AR model is utilized, where the first layer corresponds to the ordinary AR model which is block based and the second layer which is non-block based. Hierarchical modelling AR parameters, efficiently improve the compression ratio while preserving the image quality. The rest of this paper is organized as follows; the hierarchical autoregressive model with the experimental results given in sections 2 and 3 respectively.

2. **Hierarchical AutoRegressive Model (HARM**)

The HARM which is developed by Das and Lin [12] as an extension to the HARM adopted by Kakusho and Yanagida [13]. This technique implies the utilization of predictive coding once or multiple times to remove the rest of the redundancy embedded between the estimated coefficients.

The HARM simply starts from the original image, representing the root, which corresponds to layer 0, then implements the traditional predictive coding method of any order with a selected model. This constitutes the first layer. In order to construct the subsequent layer(s) (e.g., layer 2). The coefficients from the previous layer (layer 1) are regarded as an image and the predictive coding implemented on each of these parameters, and so on. As a result the top-down representation model is generated as a multi-layer or hierarchal model. By this technique we gain more compression because more decorrelation with the smallest size image coefficients but, on the other hand the more computational operation required [14], figure (1) shows this idea clearly, the layout of the encoder/decoder illustrated in figures (2) and (3) respectively.

To implement the HARM, the following algorithm had been implemented:

1. Load input uncompressed image I of size N×N.
2. Partition image I into non-overlapped blocks of sizes n×n using the fixed partitioning method due to its simplicity and popularity.
3. Construct the first layer using the traditional predictive coding techniques, where each block of size n×n in image I do :

   a. Compute the mean m and then subtract the block pixel values from m to build the stationary zero mean image W.

$$m(n,n) = \frac{1}{n \times n} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} I(i,j) \text{............}(1)$$

$$W(x,y) = I(x,y) - m(x,y) \text{........}(2)$$

b. Use a fifth order autoregressive model (i.e., 5^{th} predictor model) that's utilized by [15].

c. Estimate the predictor coefficients a using the least square method

$$a = (Z^T Z)^{-1} Z^T W \text{.......}(3)$$

Where Z is a neighborhood matrix where each row of Z consists of elements of W in an arrangement depending on the neighborhood characterizing the AR model, and a is the vector of autoregressive coefficients.

4. Construct the second layer predictive coding techniques using the previous layer (layer1) coefficients, where the second layer is built in a way that is different from the AR used in the first layer, based on the whole image rather than on a block by block basis. Also the fifth autoregressive model is adopted and the square method is utilized to estimate the coefficients.
5. Encode second layer AR coefficients information lossily.

6. Reconstruct first layer, where the process works in reverse to build or construct the up-sequence layer, (i.e., use the 2nd layer to build the 1st layer and then use the first layer to build the image).
7. Finally, the residual image e of the first layer is constructed and coded to be utilized to reconstruct the compressed or decoded image, along with the predicted image $\tilde{I}$ and the mean of each block.

$$\tilde{I} = Z.a \text{ ....(4)}$$

$$e(x,y) = W(x,y) - \tilde{I}(x,y) \text{......................(5)}$$

$$\hat{I}(x,y) = \tilde{I}(x,y) + e(x,y) + m(x,y) \text{ ....(6)}$$

3. Experiments and results

Experiments were done to evaluate the performance of the hierarchical autoregressive model (HARM) and compare it with the traditional autoregressive using a block sizes of 4×4 with various numbers of quantization levels utilized. They were selected to be between 4 and 64, using 2 to 6 bits on both the residual image and the autoregressive coefficients on a number of well-known standard images (see fig. 4 for an overview), all images of 256 gray levels (8bits/pixel) of size 256×256. The normalized root mean square error as in equation (7) between the original image I and the decoded image $\hat{I}$ was adopted as a fidelity measure, where the range of the values is between 0 and 1. A value near zero indicates high image quality, i.e. the decoded image closely resembles the original, and vice versa.

$$NRMSE(I,\hat{I}) = \sqrt{\frac{\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}[\hat{I}(x,y) - I(x,y)]^2}{\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} I(x,y)^2}} \text{........(7)}$$

Certainly, the quality of the decoded image improves as the number of quantization levels of both the autoregressive coefficients and residual image increase. The main disadvantage of increasing the quantization levels, however, lies in increasing the size of the compressed information. It is a trade-off between the desired quality and the consumption of bytes; the higher the quality required, the larger the number of quantization levels that must be used.
The experimental results are listed in table (1) showed that the best performance obtained using the HARM in terms of compression ratio, where the compression ratio improved about twice on average or more for large or less number of quantization levels respectively of both the autoregressive coefficients and residual image in the HARM techniques compared to the traditional AR. Along with preserving the image quality, this is due to the reduced AR resolution.

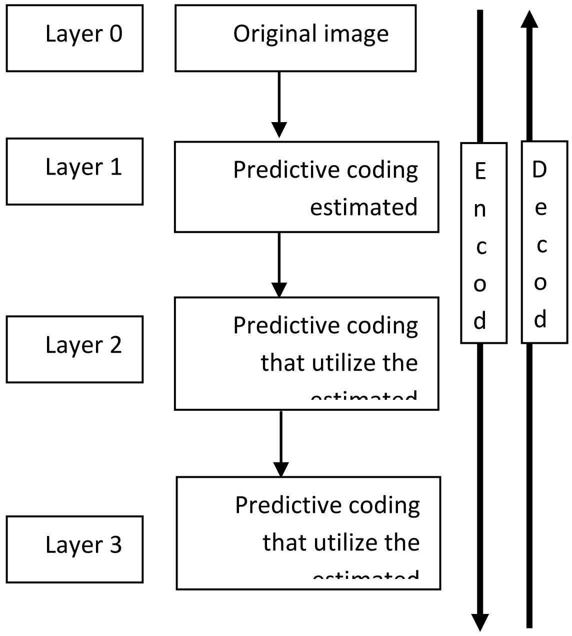

Fig. (1): Hierarchical autoregressive technique structure.

Table 1: Comparison between traditional AR and HARM in terms of Compression Ratios and Normalized Root Mean Square Errors using different quantization levels for AR coefficients and the Residual image on the tested images.

Quant.AR	Tested	Traditional AR		HARM	
Quant.Res	images	CR	NRMSE	CR	NRMSE
4 levels	Lena	2.1616	0.1452	7.9188	0.1679
(2 bits)	Girl	2.2467	0.1255	7.9669	0.1434
	Cam	2.2803	0.1751	7.9265	0.1902
	Rose	2.2419	0.1226	7.9631	0.1462
	Paper	2.5791	0.1799	7.9265	0.19959
8	Lena	2.1052	0.0790	7.6081	0.0820
(3 bits)	Girl	2.1792	0.0681	7.8168	0.0704
	Cam	2.2399	0.0990	7.6311	0.1289
	Rose	2.1993	0.1050	7.7871	0.1198
	Paper	2.5348	0.1286	7.6740	0.1407
16	Lena	2.0039	0.0449	6.8942	0.0542
(4 bits)	Girl	2.0628	0.0386	7.3487	0.0470

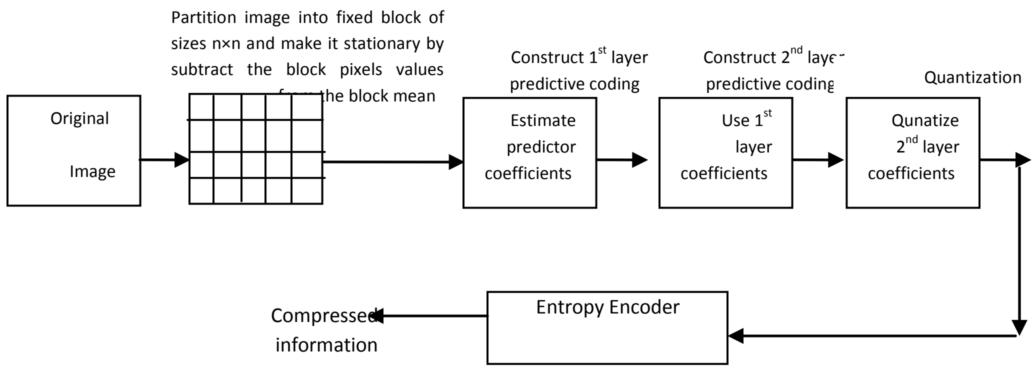

Fig. (2): Encoder structure of the proposed system

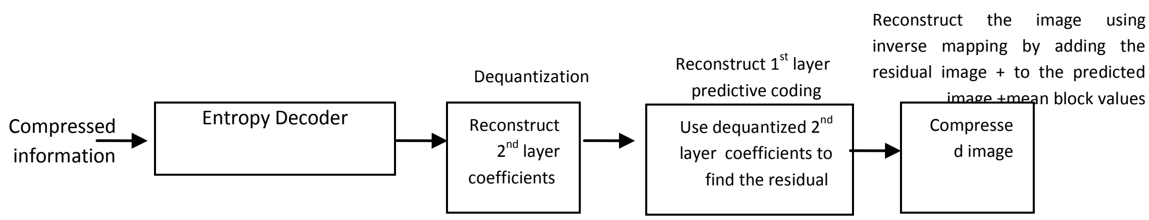

Fig. (3): Decoder structure of the proposed system

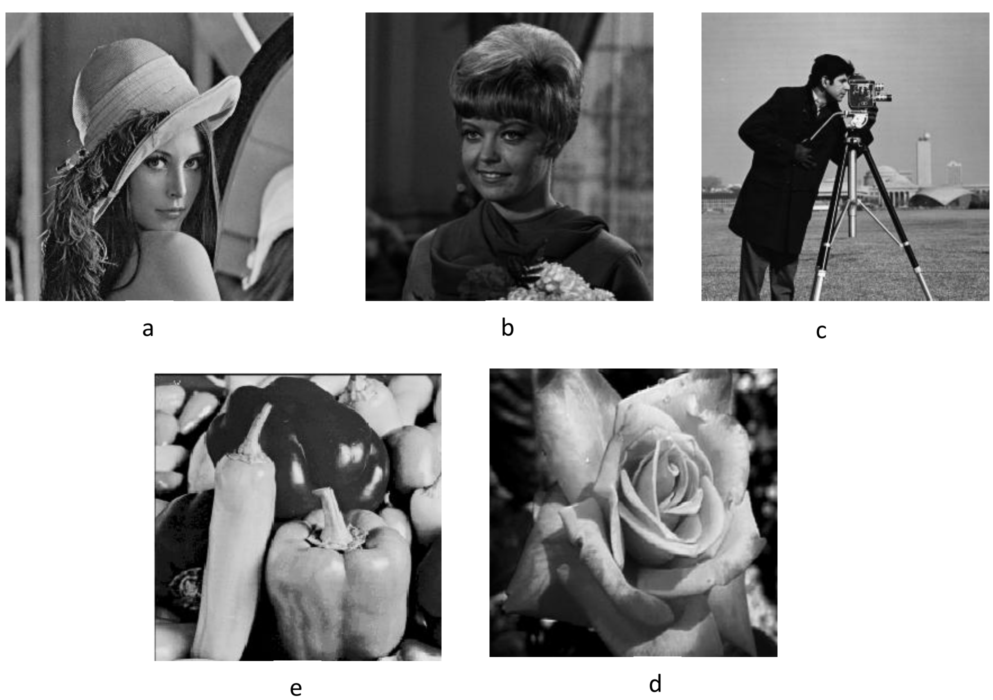

Fig. (4): Overview of the tested images (a) Lena image, (b) Girl image, (c) Camera image, (d) Rose image and (e) Paper image, all images of size 256×256, gray scale images.

References

[1] Furht, B. 1995. A Survey of Multimedia Compression Techniques and Standards. Real-Time Imaging, 1, 49-67.

[2] Singh, S. K. and Kumar, S. 2010. Mathematical Transforms and Image Compression: A Review. Maejo International Journal of Science and Technology, 4(02), 235-249.

[3] Anitha, S. 2011. 2D Image Compression Technique-A Survey. International Journal of Scientific & Engineering Research, 2(7), 1-6.

[4] Dhawan, S. 2011. A Review of Image Compression and Comparison of its Algorithms. International Journal on Electronics & Communication Technology (IJECT), 2(1), 22-26.

[5] Vrindavanam, J., Chandran, S. and Mahanti, G. K. 2012. A Survey of Image Compression Methods. Proceedings on International Conference and Workshop on Emerging Trends in Technology 12-17.

[6] Sridevi, S., Vijayakuymar, V.R. and Anuja, R. 2012. A Survey on Various Compression Methods for Medical Images. International Journal on Intelligent Systems and Applications, 3, 13-19.

[7] Das, M. and Loh, N. K. 1992. New Studies on Adaptive Coding of Images using Multiplicative Autoregressive Models. IEEE Transactions on Image Processing, 1(1), 106-111.

[8] Burgett, S. and Das, M. 1993. Predictive Image Coding using Multiresolution Multiplicative Autoregressive Models. Proceedings of the IEEE, 140(2), 127-134.

[9] Chen, Y-T. and Tseng, D-C. 2007. Wavelet-Based Medical Image Compression with Adaptive Prediction. Computerized Medical Imaging and Graphics, 31, 1-8.

[10] Eratne, S. and Alahakoon, M. 2009. Fast Predictive Wavelet Transform for Lossless Image. International Conference on Image Compression Industrial and Information Systems (ICIIS), 365–368.

[11] Mukherjee, A., Sarkar, M. and Halder, A. 2012. Predictive Lossless Color Image Compression using Arithmetic Operation. International Journal of Computer Applications, 43(5), 43-46.

[12] Das, M. and Lin, C. 1996. Lossless Compression of Medical Images Using Hierarchical Autoregressive Models. 9th IEEE Symposium on Computer-Based Medical Systems, 6-11.

[13] Kakusho, O. and Yanagida, M. 1982. Hierarchical AR Model for Time Verying Speech Signals. Proceedings of the IEEE international conference on Acoustics, Speech and Signal Processing, 1295-1298.

[14] Al-Khafaji, G. 2012. Intra and Inter Frame Compression for Video Streaming. Ph.D. thesis, Exeter University, UK.

[15] Pinykh, O.S., Tyler, J.M. and Sharman, R. 1999. Nearly-Lossless Autoregressive Image Compression. Pattern Recognition, 20, 221-228.