

Correlated Hierarchical Autoregressive Models Image Compression

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Abstract

In this paper, a *Correlated Hierarchical Autoregressive Model (CHARM)* method for image compression is proposed. It based on using multi-layered modeling concept of correlated autoregressive coefficients, which is a modified version of Hierarchical Autoregressive Model (*HARM*). The test results indicate that the suggested techniques improve the compression ratio along with preserving the image quality compared to traditional predictive coding or autoregressive model and *HARM* on a series of selected images.

Keywords: Image compression, autoregressive model and hierarchical autoregressive model

ضغط الصورة باستخدام نماذج الانحدار الهرمي المترابط

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الخلاصة

يقدم هذا البحث طريقة الانحدار الذاتي المترابط الهرمي لضغط الصور حيث انها تقوم على استخدام مفهوم النمذجة متعددة الطبقات لمعاملات الانحدار الذاتي المترابطة وهي نسخة معدلة من نموذج الانحدار الذاتي الهرمي. نتائج الاختبار تشير إلى أن التقنية المقترحة، تعمل على تحسين نسبة الضغط مع الحفاظ على جودة الصورة مقارنة بالترميز التنبؤي أو نموذج الانحدار الذاتي التقليدي ونموذج الانحدار الذاتي الهرمي على سلسلة من الصور المنتقاة.

الكلمات المفتاحية: ضغط الصور ، نموذج الانحراف المعياري، نموذج الانحراف المعياري الهرمي

Introduction

There are many different image compression techniques such as run length coding, transform coding, vector quantization, predictive coding, wavelet and fractal, see [1-5]. Today with the massive continuous revolution in communications technology and computer hardware that lead to the construction of universally accepted standard systems that play a key role in the development of compression systems. These combine efficiency, ease of use and speed with the ability to fulfil a variety of requirements, where JPEG represents the extremely useful and well-known international standard image compression techniques [6-7]. The Predictive Coding (PC) and Autoregressive (AR) are two promising techniques. They still underdevelopment even they utilized implicitly by JPEG, as well as its simple, fast and easy to implement. They generally composed of two basic steps of prediction and differentiation. In other words, they create an approximation image to the original one based on modelling the correlation or statistical dependency embedded between neighbouring pixels. Each pixel value can be predicted or estimated from nearby or neighbouring pixels, then finding the difference between the original and the predicted image, which is referred as the residual, which is normally coded because of the reduced image information compared to the original image [8-12]. Some researcher's efforts aimed to improving the traditional autoregressive model efficiency, including Ghadah [13] in 2012. She adopted selective autoregressive coding according to image features of minimum error. Hiader [14] in 2014, utilized the bitplane slicing along with autoregressive coding technique. Haider and Zainab [15] in 2014, introduced an adaptive autoregressive coding by exploiting the significant bit of image layers. Again, Ghadah and Haider [16] in 2016, adopted the selected seed techniques of autoregressive coding. Lastly, Ghadah and Hussain [17] in 2016, combined the residual of

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autoregressive model (AR) along with bit-plane slicing (BPS) to compress the medical images. In this paper, a correlated hierarchical autoregressive models of a two-layer AR model are utilized, where the first layer corresponding to the ordinary AR model of block based and the second layer of only correlated AR parameters of block based, that efficiently improving the compression ratio with preserving the image quality. The rest of this paper is organized as follows; the correlated hierarchical autoregressive model (CHARM) with the experimental results is given in sections 2 and 3 respectively.

Correlated Hierarchical Autoregressive Models (CHARM)

To remove the redundancy embedded between the estimated autoregressive coefficients (i.e., prediction coefficients), the hierarchical autoregressive model (HARM) techniques generally based on implementing the predictive coding more than one time, by exploring the autoregressive (AR) coefficients or parameters of the preceding layer. This work developed by Das and Lin in 1996 [8] as an extension to the HARM adopted by Kakusho and Yanagida in 1982 [18]. The HARM simply starts from the original image, representing the root, which corresponds to $layer_0$. Then it implementing the traditional predictive coding method of any order with the 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 generated as a multi-layer or hierarchal model. By this technique, we gain more compression because more decorrelation with smallest size image coefficients but on the other hand the more computational operation required [19].

Proposed Technique

In order to improve the performance of the HARM with less computational operation, the CHARM have been adopted as discussed in the following steps, figure (1) shows this idea clearly:

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Step1: Input the uncompressed gray image I of size $N \times N$ of *BMP* format.

Step2: Construct first layer using the traditional autoregressive coding techniques, using the following sub steps:

1. Partition the image I into blocks of fixed size $n \times n$, such as $(4 \times 4 \text{ or } 8 \times 8)$.
2. Compute the mean m of each block and then subtract the block pixel values from m to build the stationary zero mean image W .

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

$$W(x, y) = I(x, y) - m(x, y) \quad (2)$$

3. Use a fifth order autoregressive model (i.e., 5th predictor model) that utilize by Pianykh et al., [20].
4. Estimate the autoregressive coefficients (i.e., predictor coefficients) a using the least square method.

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

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

Step3: Construct second layer using the Correlated *HARM* base, such as:

1. Test the amount of correlation embedded between the previous AR coefficients ($layer_1$) the extension to the next layer depend on the subjective significant of each correlation values of the AR coefficients, where for small correlated AR coefficients there is no need to extend the process to the next layer.
2. For only correlated AR coefficients, the second layer built in an identical way to the AR used in the first layer where based on a block by block basis, with a similar extension of AR to further layers, where also the fifth autoregressive model adopted and the least square method utilized to estimate the coefficients.

Step4: Encode second layered AR coefficients information lossily.

Step5: Reconstruct first layer, where the process is worked 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).

Step6: Finally, the residual image e of the first layer is constructed, quantized 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.

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

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

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

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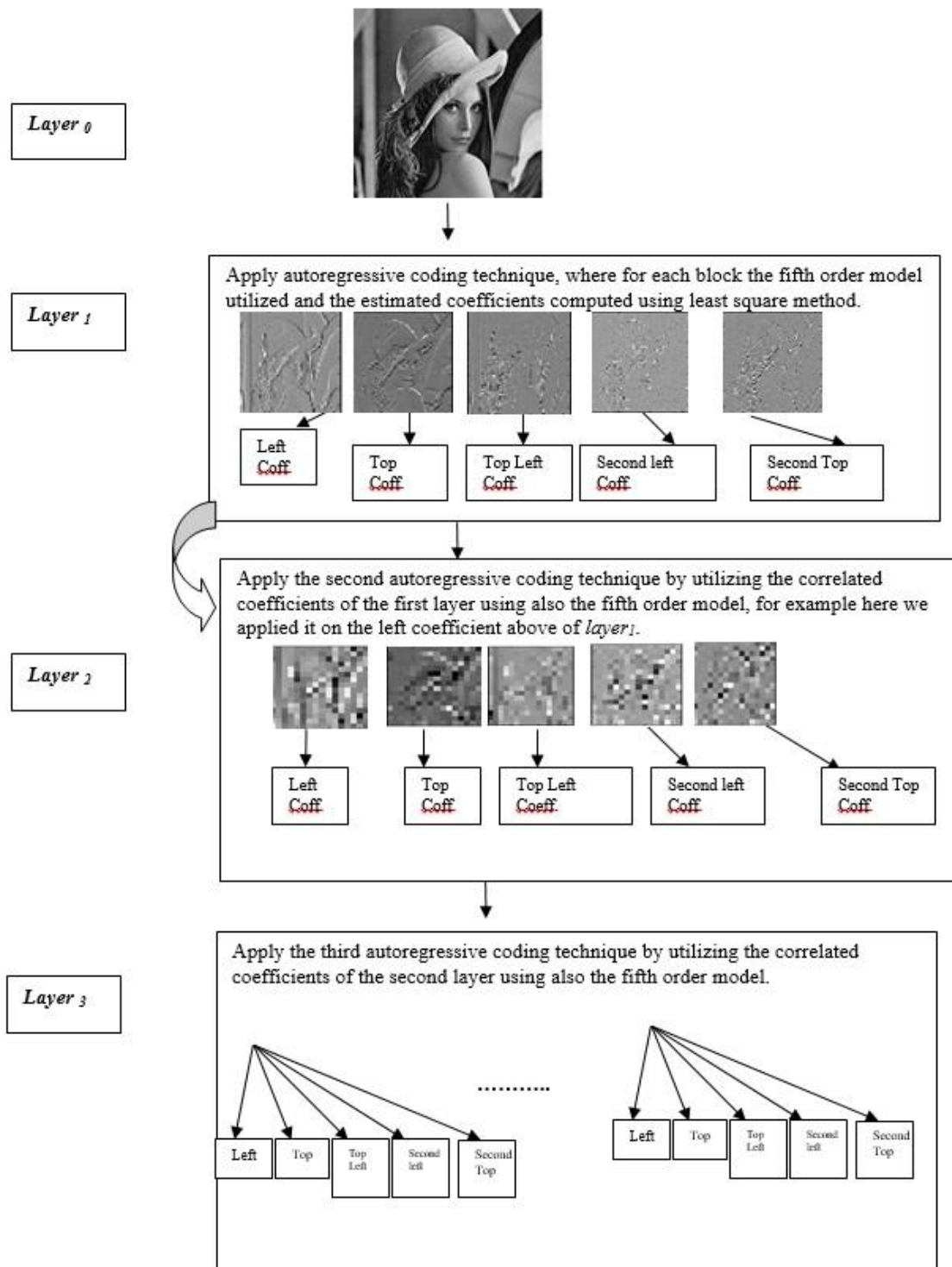


Fig. (1): Correlated hierarchical autoregressive techniques structure.

Experiments and Results

Experiments to evaluate the performance of the correlated hierarchical autoregressive model (*CHARM*) and compare it with the traditional autoregressive (*AR*) and hierarchical autoregressive model (*HARM*), using a block sizes of 4×4 with various number of quantization levels utilized was 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. 2 for an overview), all images of 256 gray levels (8bits/pixel) of size 256×256 .



Fig. (2): Overview of the tested images (a) Lena image, (b) Girl image, (c) Rose image and (d) Paper image, all images of size 256×256 , gray scale images.

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.

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

Certainly, the quality of the decoded image is improves as the number of quantization levels of both the autoregressive coefficients and residual image increase. The main disadvantage of

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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.

Figure (3) shows the autocorrelation values of the first layered AR coefficients for the mentioned standard images, which show that there is a correlation still embedded among the AR coefficients where the extension to the second layered AR required for only correlated AR coefficients.

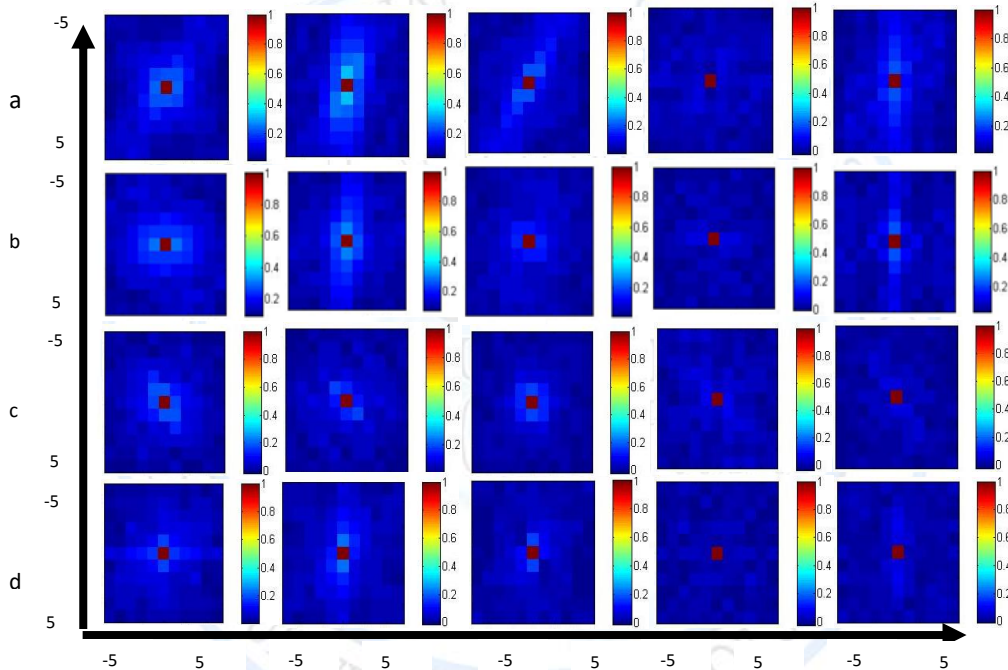


Fig (3): The autocorrelation values of first layer autoregressive coefficients of the tested images (a) Lena (b) Girl (c) Rose (d) Paper

Clearly, the autocorrelation function values of the tested images above are used as a guide to the embedded redundancy of AR coefficients, so for all the tested images the first three coefficients more correlated than the others, namely the left, top and top bottom. Figure (5) shows the autocorrelation function of the second layered AR coefficients for the tested images, which clearly illustrate that there is no need to go further to any other subsequent.

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Table 1: Comparison between traditional AR, HARM and CHARM 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 Quant.Res	Tested images	<i>Traditional AR</i>		<i>HARM</i>		<i>CHARM</i>	
		CR	NRMSE	CR	NRMSE	CR	NRMSE
4 levels (2 bits)	Lena	2.1616	0.1452	2.7144	0.1329	3.2566	0.1250
	Girl	2.2467	0.1255	2.8578	0.1142	3.4294	0.1038
	Rose	2.2419	0.1226	2.7687	0.1002	3.3079	0.0900
	Paper	2.5791	0.1799	2.7950	0.1507	3.3580	0.1306
8 levels (3 bits)	Lena	2.1052	0.0790	2.6482	0.0702	3.1568	0.0633
	Girl	2.1792	0.0681	2.7971	0.0592	3.3399	0.0578
	Rose	2.1993	0.1050	2.7175	0.0713	3.2408	0.0620
	Paper	2.5348	0.1286	2.6883	0.0813	3.2110	0.0791
16 levels (4 bits)	Lena	2.0039	0.0449	2.5179	0.0406	2.9773	0.0347
	Girl	2.0628	0.0386	2.6815	0.0352	3.1666	0.0241
	Rose	2.1342	0.0519	2.6292	0.0492	3.1269	0.0465
	Paper	2.4350	0.0579	2.5678	0.0434	3.0679	0.0416
32 levels (5 bits)	Lena	1.8386	0.0248	2.3049	0.0235	2.6699	0.0204
	Girl	1.8870	0.0206	2.4922	0.0196	2.9106	0.0191
	Rose	1.988	0.0256	2.4662	0.0240	2.9215	0.0129
	Paper	2.2541	0.0329	2.4096	0.0267	2.8363	0.0246
64 levels (6 bits)	Lena	1.6366	0.0125	2.0493	0.0119	2.2973	0.0113
	Girl	1.6737	0.0104	2.2381	0.0102	2.5463	0.0101
	Rose	1.7912	0.0127	2.2543	0.0119	2.6277	0.0108
	Paper	2.0031	0.0170	2.1758	0.0143	2.5158	0.0136

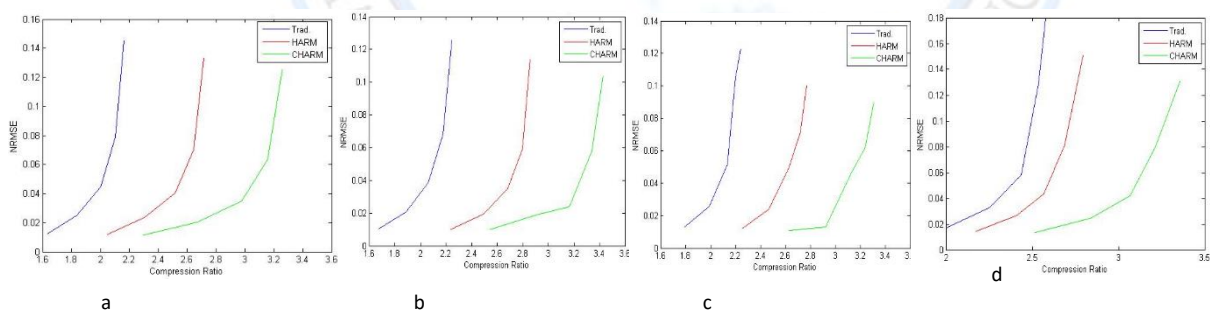


Fig. (4): Compression ratio versus the normalized mean square error of the tested images (a) Lena (b) Girl (c) Rose (d) Paper using traditional PC, HARM and CHARM

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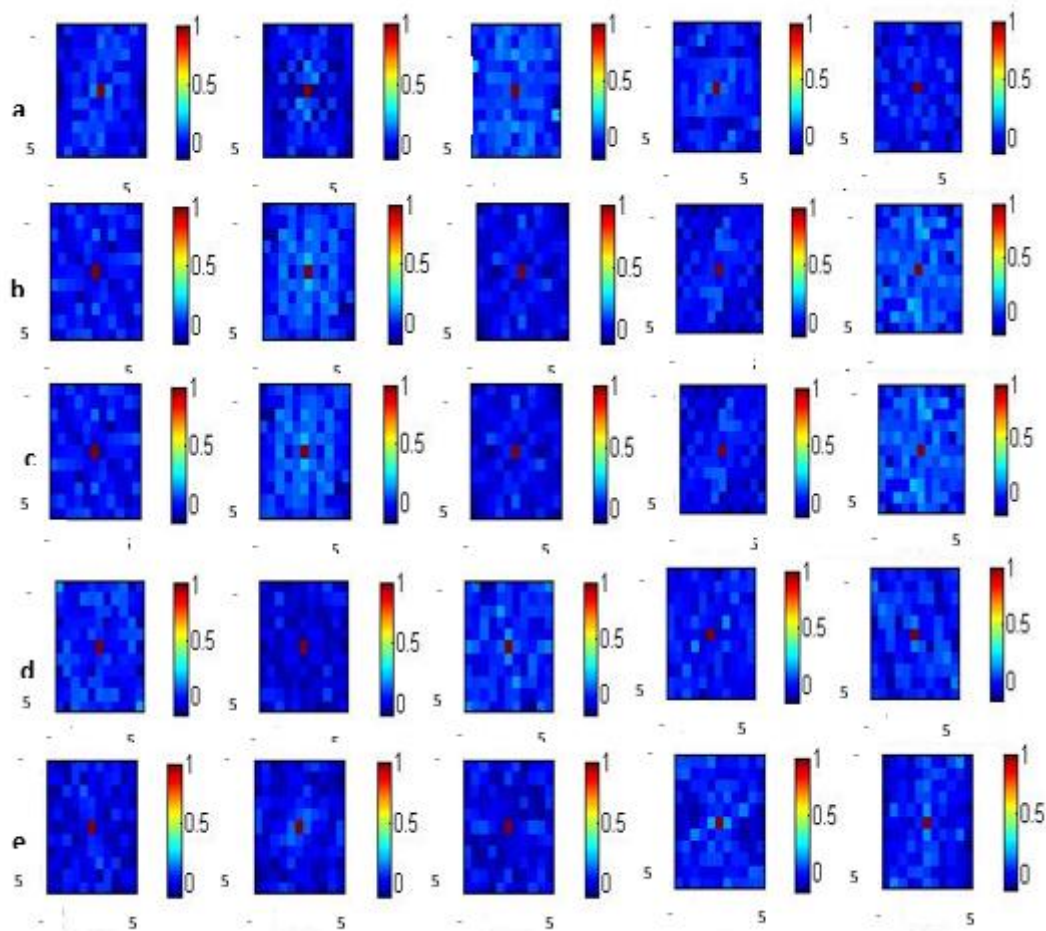


Fig. (5a): Second layer autocorrelation function for the Lena image, where (a) 2nd layered left AR coefficients (b) 2nd layered top AR coefficients (c) 2nd layered top-left AR coefficients (d) 2nd layered 2nd left AR coefficients and (e) 2nd layered 2nd top AR coefficients, where each composed of five images corresponds to left, top, top-left, 2nd left and 2nd top.

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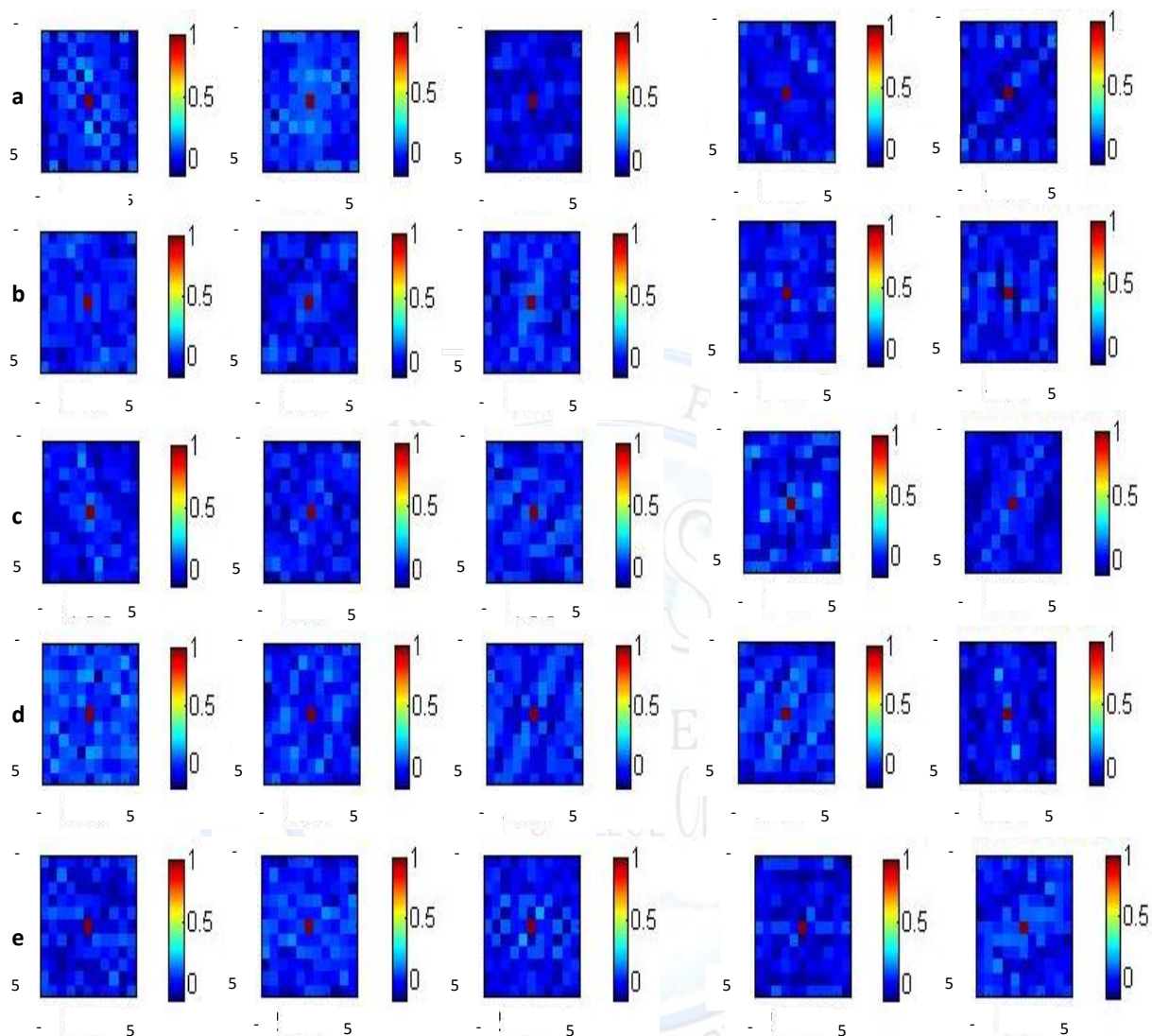


Fig. (5b): Second layer autocorrelation function for the Girl image, where (a) 2nd layered left AR coefficients (b) 2nd layered top AR coefficients (c) 2nd layered top-left AR coefficients (d) 2nd layered 2nd left AR coefficients and (e) 2nd layered 2nd top AR coefficients, where each composed of five images corresponds to left, top, top-left, 2nd left and 2nd top.

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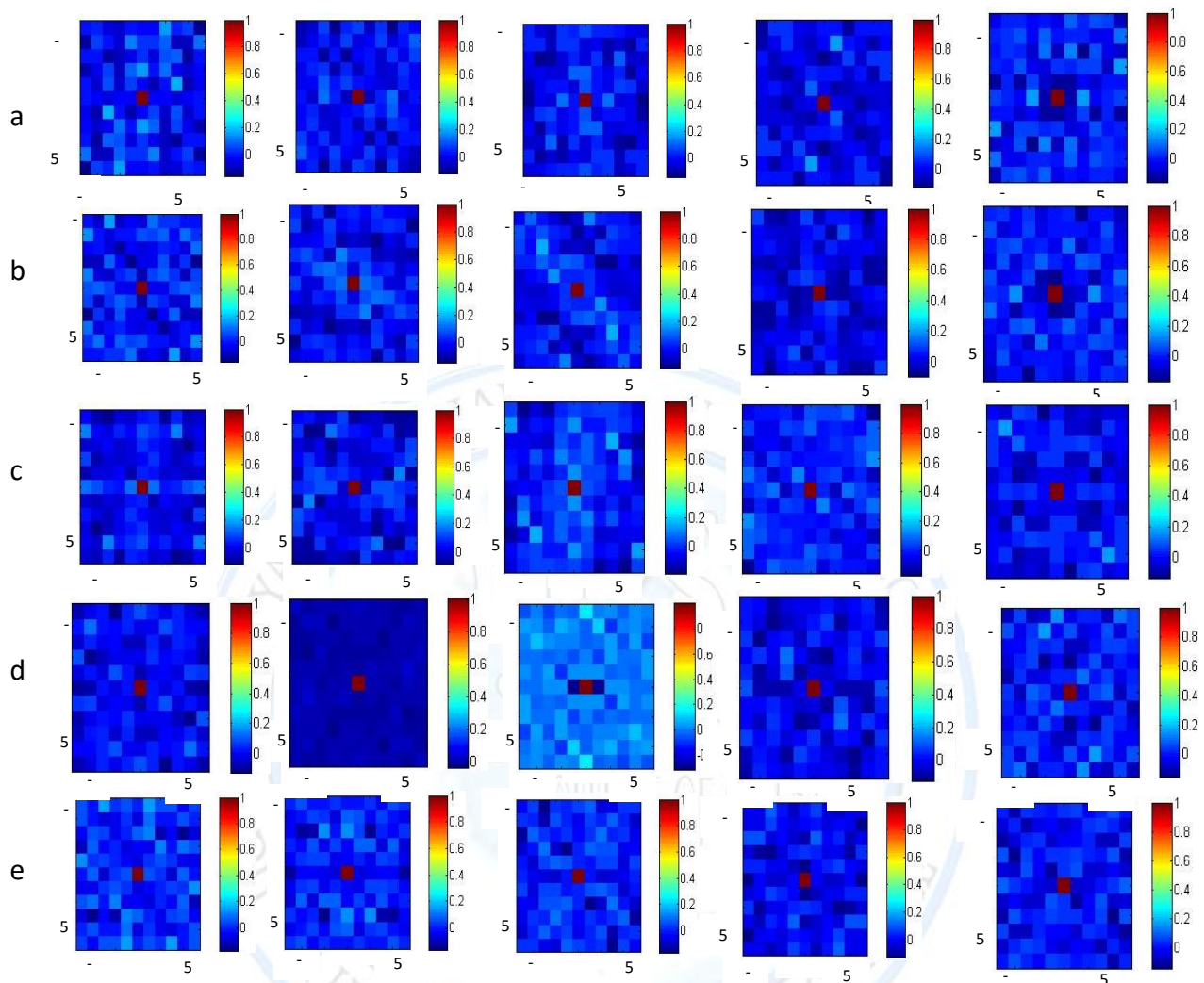


Fig. (5c): Second layer autocorrelation function for the Rose image, where (a) 2nd layered left AR coefficients (b) 2nd layered top AR coefficients (c) 2nd layered top-left AR coefficients (d) 2nd layered 2nd left AR coefficients and (e) 2nd layered 2nd top AR coefficients, where each composed of five images corresponds to left, top, top-left, 2nd left and 2nd top.

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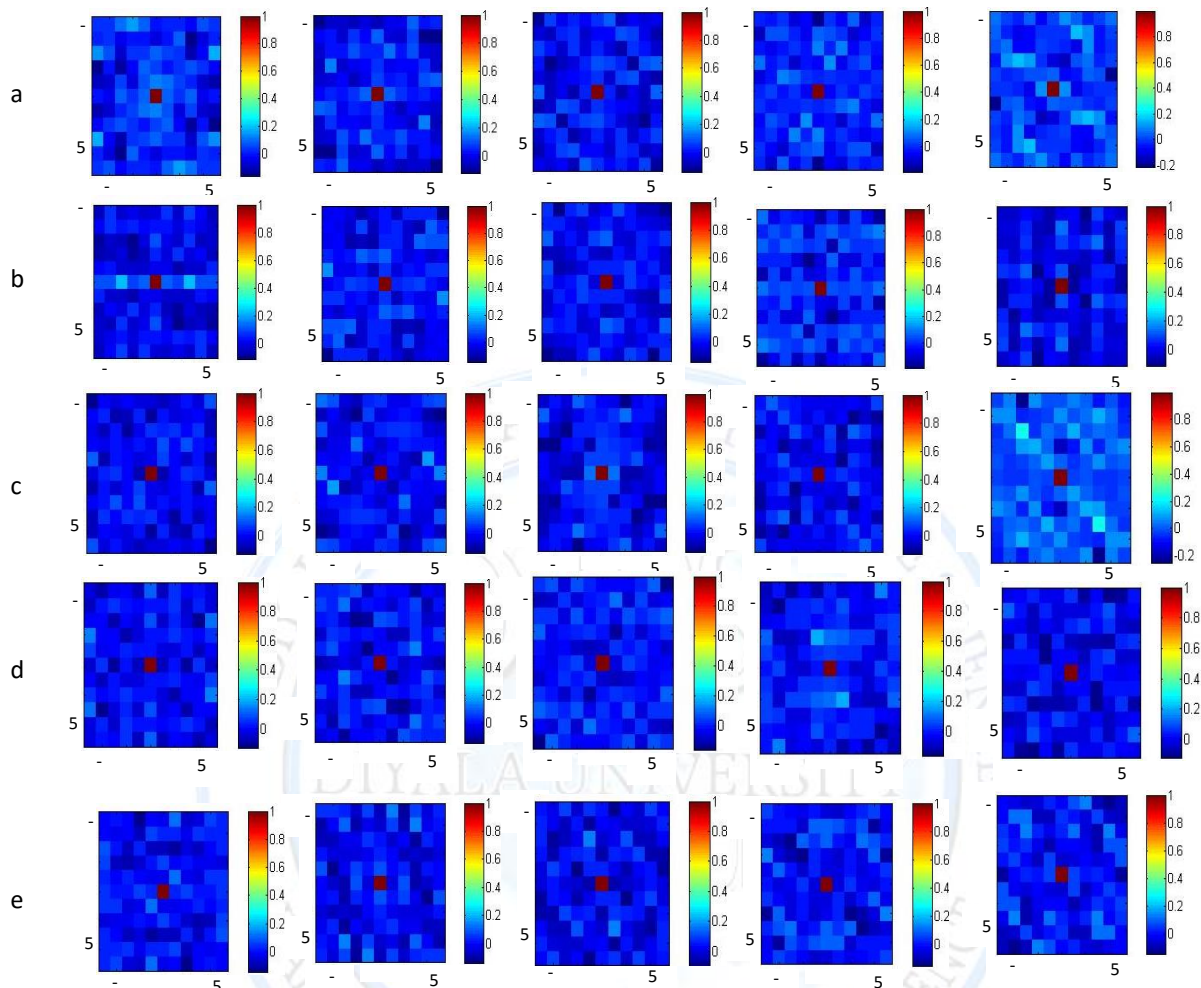


Fig. (5d): Second layer autocorrelation function for the Paper image, where (a) 2nd layered left AR coefficients (b) 2nd layered top AR coefficients (c) 2nd layered top-left AR coefficients (d) 2nd layered 2nd left AR coefficients and (e) 2nd layered 2nd top AR coefficients, where each composed of five images corresponds to left, top, top-left, 2nd left and 2nd top.

Conclusions

The experimental results listed in table (1) and Figure (4), showed that the best performance obtained using the *CHARM* in terms of compression ratio and quality, for all the tested images. That is due to the reduced resolution of correlated *AR* coefficients, which based on modelling the correlated *AR* coefficients of the previous layer, and leaving less correlated coefficients without extend.

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