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Bit-Plane Slicing Autoregressive Modeling for Medical Image Compression

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Abstract
In this paper, a simple medical image compression technique is proposed, that based on utilizing the residual of autoregressive model (AR) along with bit-plane slicing (BPS) to exploit the spatial redundancy efficiently. The results showed that the compression performance of the proposed techniques is improved about twice on average compared to the traditional autoregressive, along with preserving the image quality due to considering the significant layers only of high image contribution effects.

Keywords: Image compression, autoregressive coding and bit-plane slicing.

نموذج تشريح البتات والانحدار الذاتي لضغط الصور الطبية

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الخلاصة:
يقدم هذا البحث طريقة بسيطة لضغط الصور الطبية والتي تعتمد على استخدام الباقي لتقنية الانحدار الذاتي مع نموذج تشريح البتات للصورة والتي تعمل على استثمارالتكرار الحيزي بكفاءة. اظهرت النتائج تفوق اداء نسب ضغط الطريقة المقترحة تقريبا مرتين كمعدل مقارنة مع نموذج الانحدار الذاتي التقليدية مع المحافظه على جودة الصورة الناتجة وهذا يعود لاستخدام الشرائح المهمة ذات التاثير المهم على تفاصيل الصورة.

1. Introduction

Lossless techniques usually exploit statistical redundancy alone without losing information that mean preserving image quality perfectly. The lossless image compression, widely most commonly with medical applications, due to essential need to identically, in which the compressed image can be reconstructed exactly as the original one where information is lost (i.e., error free base) [1], reviews of medical image compression techniques can be found [2-4].

The traditional autoregressive technique is a promising technique for image compression, still under development, and not yet a recognized standard like JPEG even it is used by the main image and video coding standards. The techniques characterized by simplicity, symmetry of the encoder and decoder and flexibility of use [5], for general information on the technique see [6-8].

Recently, a large number of researchers have exploited the autoregressive technique to compress images, including Selective autoregressive coding [1] that proposed by Ghadah in 2012, based on selecting some prediction models depending on the image features (twelve's selected predictors), then computing the residuals between these predictors and the original image. Once have these residual images, construct the selective residual image with lowest error block values (block by block), where the block with the lowest minimum error is selected. Followed by performed the traditional autoregressive (AR) model on this selective residual image, technique leads to high efficiency performance.

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On the other hand, adaptive selective autoregressive coding [1] introduced by Ghadah in 2012, is an improvement of selective coding adopted by [7, 9] of fixed and various predictor(s) respectively. Moreover, the hierarchical autoregressive model [1] adopted by Ghadah in 2012, based on implementing the autoregressive coding more than once, by exploring the autoregressive coefficients or parameters of the preceding layer, where the efficient performance indicated[10]. Utilized the classification principles to classify the blocks according to nature, where for smoothed blocks smaller number of coefficients required compared to unsmoothed blocks, where the high compression performance achieved. Variable block sizes of quadtree base instead of utilizing the fixed partitioning scheme, the results promising due to locality principle [11,12], combined the techniques of wavelet, linear polynomial coding and the bit plane slicing is integrated to improve the lossless image compression performance[13]. Used adaptive selective autoregressive bit plane slicing mode [14], exploited the bit-plane slicing and adaptive autoregressive coding, where the idea basically utilized the spatial domain efficiently after discarding the lowest order bits namely, exploiting only the highest order bits in which the most significant bit corresponds to last $layer_7$ used adaptive predictive coding, while the other layers used run length coding. The test results leads to high system performance in which higher compression ratio achieves for lossless system that characterized by guaranty fully reconstruction [15]. Proposed a hybrid effective compression technique. Lastly [16], adopted enhanced autoregressive coding technique based on utilizing two effective selection seed values algorithms

In this paper, the adaptive autoregressive coding is proposed that based on utilizing only the spatial domain efficiently that combines the autoregressive coding (*AR*) and bit plane slicing (*BPS*), to improve the compression performance by exploiting the most significant bits (*MSB*) of residual image. The adaptive techniques discussed in section 2 and the results are given in section 3.

2. The Proposed System

This paper is concerned with utilizing the residual (probabilistic part) along with bit plane slicing (*BPS*) of the spatial redundancy base that characterized by simplicity and efficiency. The steps below explain the proposed system and depicted by Figure-1.

Step 1: Load the input uncompressed gray image *I* of *BMP* format of square size $N \times N$.

Step 2: Partition the image (*I*) into non overlapped blocks of fixed size $n \times n$, such as (4×4) or (8×8).

Step 3: Choose the third order, two dimensional causal mathematical models, as shown in Figure-2.

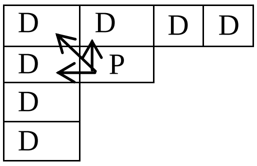

Figure 2- Third order, two dimensional causal model, *P* means predicted values depends on the pixels to the left, bottom, left-bottom [17].

Step 4: Compute the mean *m* for each segmented block in the image *I* and then subtract the block pixel values from *m* to reach to the stationary state to ensure accuracy of prediction.

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

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

Here *W* denotes a local zero mean image, *m* denotes a block local mean and *I* the original uncompressed image.

Step 5: Compute the autoregressive coefficients using least square method for each block in image *W* according to equation (3).

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

Here a refers to the autoregressive coefficients or weights (model factor) and 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 [1].

$$\underbrace{\begin{bmatrix} \cdots \\ \cdots \\ \tilde{I}(3,3) \\ \tilde{I}(3,4) \\ \tilde{I}(3,5) \\ \cdots \\ \cdots \\ \cdots \\ \cdots \\ \tilde{I}(n,n) \end{bmatrix}}_{I} = \underbrace{\begin{array}{c} \begin{array}{ccc} \quad \text{L} \quad & \quad \text{T} \quad & \quad \text{LT} \quad \end{array} \\ \begin{bmatrix} \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ w(3,2) & w(2,3) & w(2,2) \\ w(3,3) & w(2,4) & w(2,3) \\ w(3,4) & w(2,5) & w(2,4) \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ W(I,j-1) & W(i-1,j) & W(i-1,j-1) \end{bmatrix} \end{array}}_{Z} \underbrace{\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}}_{a}$$

Step 6: Create the predicted image $\tilde{I}$ as in equation below.

$$\tilde{I}(x,y) = (a_1 W(x-1,y) + a_2 W(x,y-1) + a_3 W(x-1,y-1) \qquad (4)$$

Here $\tilde{I}$ is the predicted image, *W* is the local zero mean image, (a_1, a_2 and a_3) the autoregressive coefficients (parameters).

Step 7: Find residual image e between W and $\tilde{I}$ by equation:

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

Here e is the residual image, *W* is a local zero mean, $\tilde{I}$ is the predicted image.

Step 8: Apply the mapping process by converting the negative and positive values into positive values only either even or odd, using the mapping formula below [18].

$$Map\,\mathrm{Re}\,s = \begin{cases} 2\,\mathrm{Re}\,s & \text{if Res} \geq 0 \\ 2|\mathrm{Re}\,s| - 1 & \text{else Res} < 0 \end{cases} \qquad (6)$$

Here $Map\,\mathrm{Re}\,s$ is the value of the mapped residual image, where the negative values mapped to odd while the positive values mapped to even.

Step 9: Slice the mapped residual image into its layers according to the image intensity value, where the bit plane slicing separating it into eight layers, where the least significant layers (*LSLs*) arranged from $layer_0$ to $layer_3$, while the most significant layers (*MSLs*) from $layer_4$ to $layer_7$.

Step 10: Remove the low or small image contribution effects by discarding the least significant layers (*LSLs*) and keeping only the most significant layers (*MSLs*) of highly effect. (i.e. use only 4 slicing layers).

Step 11: Use Huffman coding to compress the most significant layers (*MSLs*) of mapped residual image, the estimated coefficients and the mean of each block.

Step 12: Reconstruct identical compressed image I , by first applying the inverse mapping process, to map each value into equivalent representation [10], by applying the following then adding the predicted and the mean:

$$InvMap\,\mathrm{Re}\,s = \begin{cases} Map\,\mathrm{Re}\,s/2 & \text{if even} \\ (Map\,\mathrm{Re}\,s + 1)/2 & \text{else odd} \end{cases} \qquad (7)$$

$$I(x,y) = \tilde{I}(x,y) + InvMap\,\mathrm{Re}\,s(x,y) + m(x,y) \qquad (8)$$

Here I is the decoded compressed image that identical to the original image, $\tilde{I}$ is the predicted image, $InvMap\,\mathrm{Re}\,s$ is the inverse mapping residual image, and *m* is the local mean.

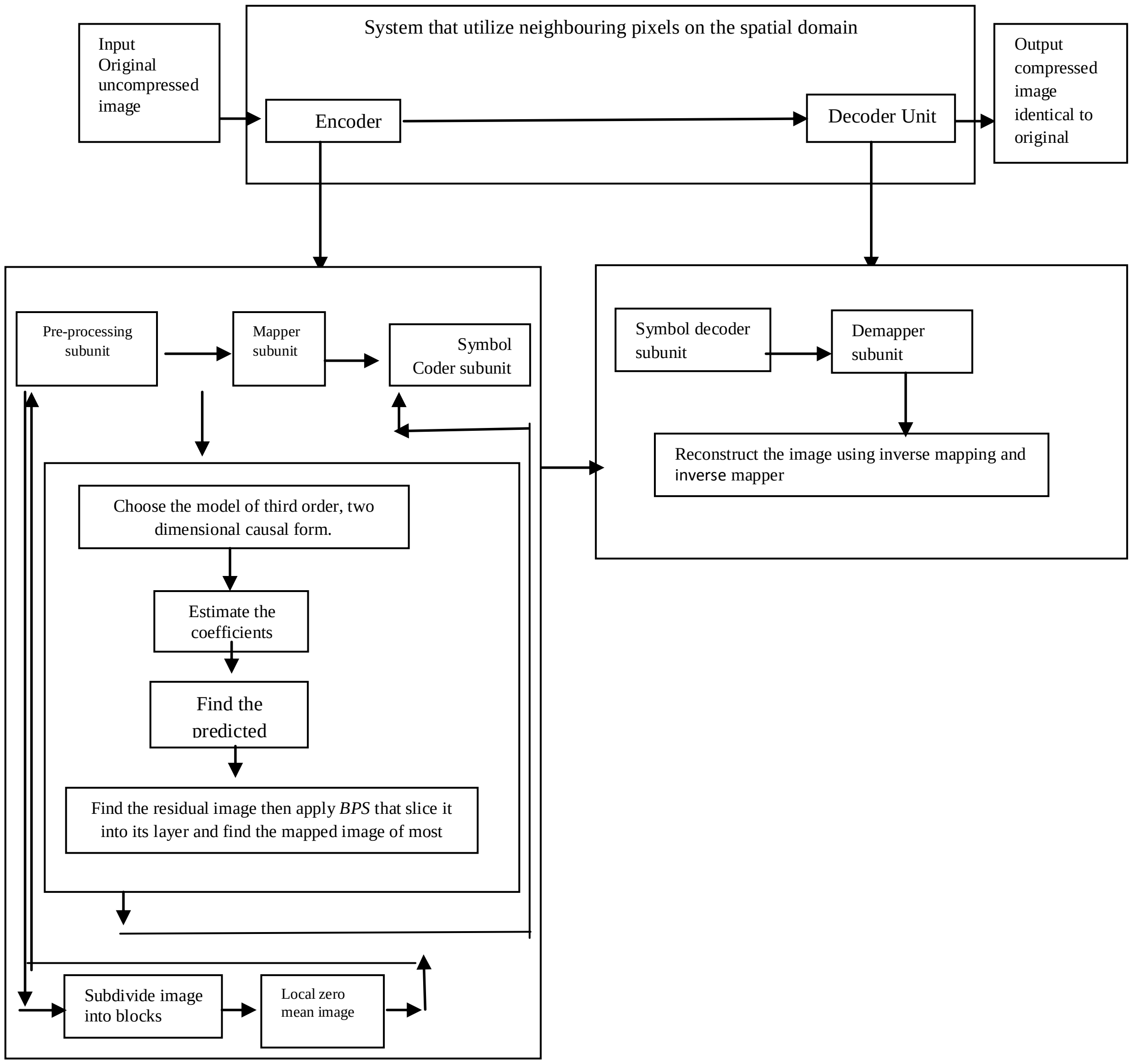

Figure 1- The block diagram of the proposed system.

3. Results and Discussion

For testing the proposed system performance adaptive autoregressive (AAR) and compare it with the traditional autoregressive (TAR), it's applied to a number of medical images of different types (see Figure-3 for an overview), all the images are gray of 256 gray levels (8bits/pixel) of size 256×256 and using a block sizes of 8×8.

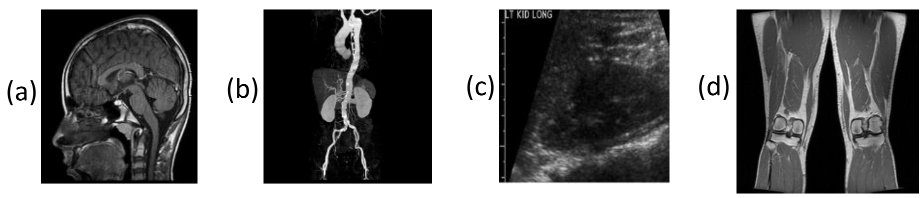

Figure 3 -The tested images of size 256×256 (a) Brain (b) Tummy (c) Echo (d) knee.

The experimental results are listed in Table -1 showed that the best performance obtained using the AAR (Adaptive Autoregressive) in terms of compression ratio, where the compression ratio improved about twice on average compared to the TAR (Traditional Autoregressive) for the tested images, this due to the removal of the redundancy embedded on the resultant residual image using the bit plane slicing technique by neglected least significant layers (*LSLs*) of small contribution effects of image details. Also the results vary according to image details, since the technique is absolutely spatial domain utilization technique. Lastly, the simple encoder of Huffman coding techniques of probability based utilized due to simplicity and popularity. The traditional autoregressive do not contain an error so identical with compute peak signal-to-noise ratio (PSNR) = Infinity.

Table 1-The medical compression performance for the tested images

Tested Images	Size in bytes of Original image	Block Size 8×8			
		Traditional (AR)		Adaptive (AR)	
		PSNR	Compression Ratio	PSNR	Compression Ratio
Brain (MR)	65536	∞	3.0285	76	5.1628
Echo (US)	65536	∞	3.2034	74	6.0026
Tummy (MR)	65536	∞	4.1903	72	5.4135
Knee (MR)	65536	∞	3.6810	78	6.2344

4. Conclusions

This paper attempts to exploit the residual part of autoregressive coding efficiently using the bit plane slicing technique by utilizing the most significant layers (*MSLs*) only of highly effect of image details, where the mapping process constitutes the core that preserve the residual image information effectively. The experimental results clearly showed improvements in performance for adaptive autoregressive coding compared to traditional autoregressive coding techniques.

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