Medical Image Compression based on Polynomial Coding and Region of Interest

Asst. Prof. Dr. Ghadah Al-Khafaji[1]* and Anhar Sami [2]*
[1] Department of Computers, College of Science, University of Baghdad, Baghdad, Iraq.
[2] Department of Computers, College of Science, University of Baghdad, Baghdad, Iraq.
[1]*Hgkta2012@scbaghdad.edu.iq, hgkta2012@yahoo.com*
[2]*Anhar.sami@muc.edu.iq*

Abstract

Medical imaging (*MI*) plays a major role in contemporary health care, both as a tool in primary diagnosis and as a guide for surgical and therapeutic procedures. The trend in *MI* is increasingly ubiquitous, where digital data do not suffer from aging and moreover are suited to archived, stored and retrieved quickly and reliably, but unfortunately there is huge byte consumptions.

Image compression refers to reduce the amount of data in an image for storing or transmitting it in an efficient form. Generally, this can be achieved by removing redundant or irrelevant information and keeping only the relevant information.

The medical image compression techniques, currently exploited the region of interest (*ROI*) concept, sometimes there's important region of the image rather than the whole image, where segregate the required region from the image play a vital role.

The first part of this paper exploits the traditional polynomial coding techniques modeling based to compress gray scale medical image losslessly. The Second part aims at enhancing the performance of the medical coding techniques, by incorporating the *ROI* of hybrid base, where lossless polynomial coding used for *ROI* portion and the scalar uniform quantizer for non-*ROI* portion, also the *ROI* utilized according to image nature which either of simple edge based one, or threshold complex feature based.

The tested results shown are promising in terms of high compression ratio and preserving the quality perfectly, with efficiently separate the *ROI* portion by utilizing the edge and beneficial features of the object.

Key words: medical imaging, image compression, polynomial coding, and region of interest.

1. Introduction

Medical imaging (*MI*) it also known as diagnostic imaging lie at the heart of healthcare [1], that had a great impact on the diagnosis of diseases and surgical planning [2]. Various medical digital images available either in two dimension or three dimension forms depending on the application such as magnetic resonance (*MR*), ultrasound (*US*), computerized tomography (*CT*), nuclear medicine (*NM*), positron emission tomography (*PET*), digital subtraction angiography (*DSA*) and X-rays images [1].

Today the *2D* medical imaging dominates the use due to its simplicity, lowest cost and resolution efficiency, but unfortunately comes with large number of bits required [1], that data compression has lately become more vital to efficient storage and transmission [2, 3].

Reducing the medical image size represents the core of lossless image compression type that characterized by preserving the information; where the image can be reconstructed exactly as the original in which no information is lost, where no loss of relevant information is allowed [1]. Generally, it is possible to do lossless compression with techniques such as Huffman coding, Arithmetic coding, Lempel-Ziv, Differential Pulse Code Modulation and Multiresolution techniques; but most of these methods leads to limited compression ratio results [1]. Reviews of medical image compression techniques and a comparison in performance of several different lossless techniques on various medical image types can be found in [4-8].

Current compression schemes produce high compression rates if loss of quality is affordable. However, medicine cannot afford any deficiency in diagnostically important regions. Region of interest (*ROI*), an approach that brings a high compression ratio with good quality in the *ROI* is thus necessary. A hybrid-coding scheme seems to be the only solution to this twofold problem. The general theme is to preserve quality in diagnostically critical regions, while allowing loss encoding the other regions. The main reason for preserving regions other than *ROI* is to let the viewer more easily locate the position of the critical regions in the original image, and to evaluate possible interactions with surrounding organs [9].

In this paper we focus on efforts aimed at improving the medical image compression using the polynomial coding and *ROI* concept, where for the former including Ghadah and Loay (2013) [10], which introduced a fast lossless compression techniques of medical images based on polynomial coding where the blocks classified according to its nature, where for smoothed blocks smaller number of coefficients required compared to unsmoothed blocks, where the improved of compression performance is achieved. Ghadah and Hazim (2014) [11], also adopted the polynomial coding and bit plane slicing techniques to compress medical images according to correlation embedded of each wavelet quadrants. The test results showed elegant performance of lossless image compression techniques. Ghadah and Maha (2016) [12], suggested a combination between the lossless and lossy polynomial image compression techniques as a new hybrid image compression system of the lossless non-linear polynomial coding base and lossy linear polynomial base. The results indicate the excellent performance achieved, in terms of higher compression ratio and medical image quality. Abdullah (2018) [13], applied the hierarchal scheme to compress gray scale images losslessly efficiently, that presents the mixing of even and odd hierarchal decomposition effectively along the input image, the coefficients, the residual and the combination between them, the results promising due to separation base. For the latter including Lavanya and Suresh (2013) [14], which utilized *ROI* of edge based that is divided into three regions, namely primary region, secondary region, and background region, where lossless compressions are applied over primary and lossy to secondary and background. Mary and Chitra (2016) [15], introduced a region of interest(*ROI*) based compression method of block based along with Vector Quantization(*VQ*) to enhance the image quality for efficient transmission and storage. Palak and Dhruti (2016) [16], adopted *ROI* of saliency map technique, after that targets or ROIs be coded at available bits while the remainder of the background or *Non-ROI* part is coded using fewer bits. David et. al. (2017)[17], exploited the two segmentation processes where the first one of object based segmented the medical image into *ROI* and *Non-ROI*, while the second segmented classify block according to its nature of complexity.

This paper is concerned with improving the medical image compression performance using the *ROI* and polynomial coding scheme to compress gray scale images as mixing between lossless and lossy base's efficiently, where the *ROI* utilized either of simple edge based one, or threshold complex feature based according to image of stationary or non-stationary background images. The rest of paper organized as follows, sections 2 and 3 contains comprehensive clarification of the traditional and proposed systems; the results for the proposed system and the conclusions, is given in sections 4 and 5, respectively.

2. Medical image compression using Traditional Linear Polynomial Coding Technique

The polynomial coding, based on modelling concept to remove the spatial (inter-pixel) redundancy effectively, are basically composed of two basic steps of prediction and differentiation, that mainly concerned with the capability of mathematical model to represents image information efficiently with a small number of coefficients and low residual that leads to packing or compressing image compactly [13,18-22]. Namely, to compress a medical image, let's assume an original input uncompressed image I of size $N \times N$,to capture or exhibit the local correlation between neighbouring pixels, the non-overlapping needs, generally the fixed partitioning scheme adopted to block of sizes ($n \times n$). After this stage, the coefficients estimated according to equations below (1-4), then the residual, or prediction error, is calculated between the original image pixel values and the predicted image (see equations 5&6), finally the residual image and coefficients are losslessly encoded. Figure (1) shows the polynomial coding system structure in more detail

$$a_0 = \frac{1}{n \times n} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} I(i,j) \qquad (1)$$

$$a_1 = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} I(i,j) \times (j - x_c)}{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (j - x_c)^2} \qquad (2)$$

$$a_2 = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} I(i,j) \times (i - y_c)}{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (i - y_c)^2} \qquad (3)$$

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

$$\tilde{I} = a_0 + a_1(j - x_c) + a_2(i - y_c) \qquad (5)$$

$$\mathrm{Re}\,s(i,j) = I(i,j) - \tilde{I}(i,j) \qquad (6)$$

Where a_0 coefficient corresponds to the mean (average) of block of size ($n \times n$) of original image *I*. The a_1 and a_2 coefficients represent the ratio of sum pixel multiplied by the distance from the center to the squared distance in *i* and *j* coordinates respectively, and the (*j*-*xc*) and (*i*-*yc*) corresponds to measure the distance of pixel coordinates to the block center (*xc*, *yc*). Also $\tilde{I}$ denotes a predicted image and *Res* represents the residual image.

The decoder exploits the information received from the encoder to reconstruct the image, by first utilizing the coefficients to build a predicted image using the identical encoder predictor, and then adding to the residual, such as:

$$I(i,j) = \tilde{I}(i,j) + \mathrm{Re}\,s(i,j) \qquad (7)$$

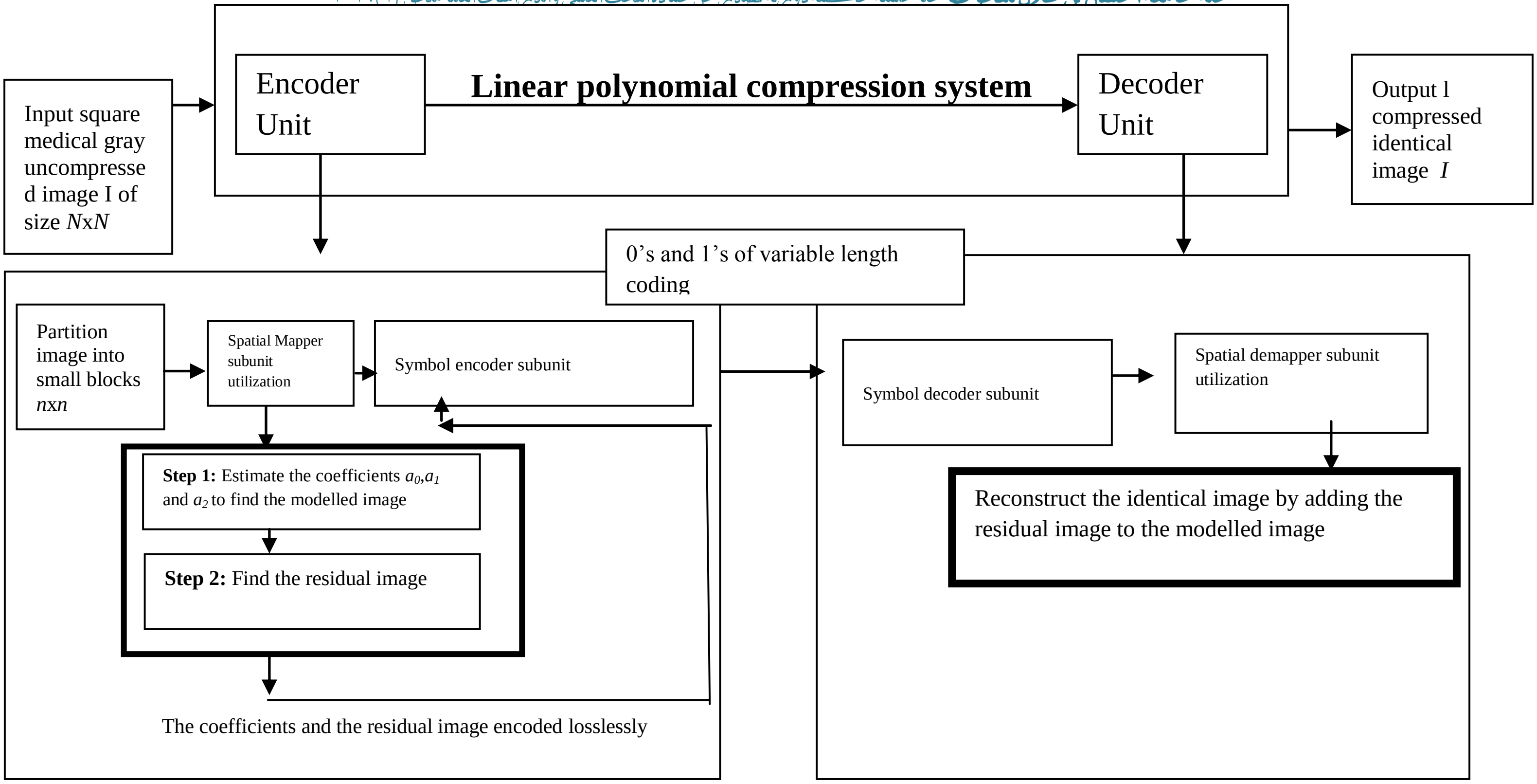


Figure (1): The linear polynomial model structure of lossless base [9].

3. Medical image compression using ROI and Traditional Linear Polynomial Coding Technique

This section improves the polynomial coding performance using the ROI concept. The following subsections 3.1, and 3.2 encompassing ROI using edge and thresh holding based techniques respectively.

The core principle of ROI coding techniques, it is based on implementing hybrid compression methods efficiently that the lossless compression used for ROI region and the lossy compression for non-ROI region

3.1 ***Medical image compression using Traditional Linear Polynomial Coding with Single ROI on a stationary background of Edge based Technique***

As mentioned previously the medical images it also known as diagnostic imaging lie at the heart of healthcare [1], mostly these images characterized by a fixed black background that can be easily separated from the foreground, and the object that corresponding to the ROI appears relatively centroid the image content. Therefor the segmentation process of edge based efficiently used to separate the ROI that can modeled using polynomial coding coefficients lossless, while the black background quantized and coded lossy.

The idea relies on utilizing the simple edge segmentation based technique to extract ROI from non-ROI- background, as shown in illustrative figure example (2), and then implementing the polynomial coding techniques to the ROI. The proposed system implantation is depicted in figure (3), and the following steps are applied.

Step 1: Load the input uncompressed medical gray image *I* of *BMP* format of size *N*×*N*.

Step 2: Finding image edges using the Sobel operator by convolving the image with a small, separable, and integer-valued filter of (3x3) in the horizontal and vertical directions where the gradient computed and the resultant binary image, in which the zeros corresponding to non-edge image pixels and the ones corresponding to edge image pixels.

Step 3: Find the selected region automatically that corresponding to ROI using the resultant binary image from the step above, the process starts by finding all the edge points with pixel values equal to ones, then finding the maximum and minimum values of horizontal and vertical directions and lastly commuting the width and height of the selected important regions according to equation below

$$Wid_{ROI} = Maximum_x - Minimum_x \qquad (8)$$

$$Hgt_{ROI} = Maximum_y - Minimum_y \qquad (9)$$

Where Wid_{RoI} and Hgt_{ROI} corresponding to width and height of ROI.

Step 4: Apply the Polynomial coding technique to the selected ROI lossless (see section 2).

Step 5: Quantize the background region into two level quantization image (binaryimage of 1 bpp) using the scalar uniform quantizer of lossy base.

$$QNon-ROI = round\left(\frac{Non-ROI}{QS_{Non-ROI}}\right) \rightarrow DNon-ROI = QNon-ROI \times QS_{Non-ROI} \text{........}(10)$$

Step6: Encode the compressed image information of ROI and non-ROI, namely the polynomial coefficients and the residual image with zeros of background image.

To reconstruct the approximated medical compressed image of high quality $\hat{I}$,using the ROI and non-ROI regions together, where for the former implies adding the predicted image to the residual one, while the latter implies dequantization process.

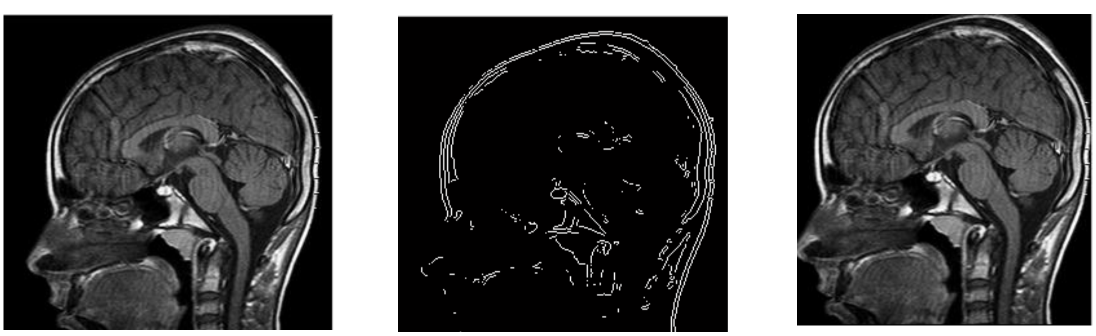


Figure (2): The practical example of the edge based ROI

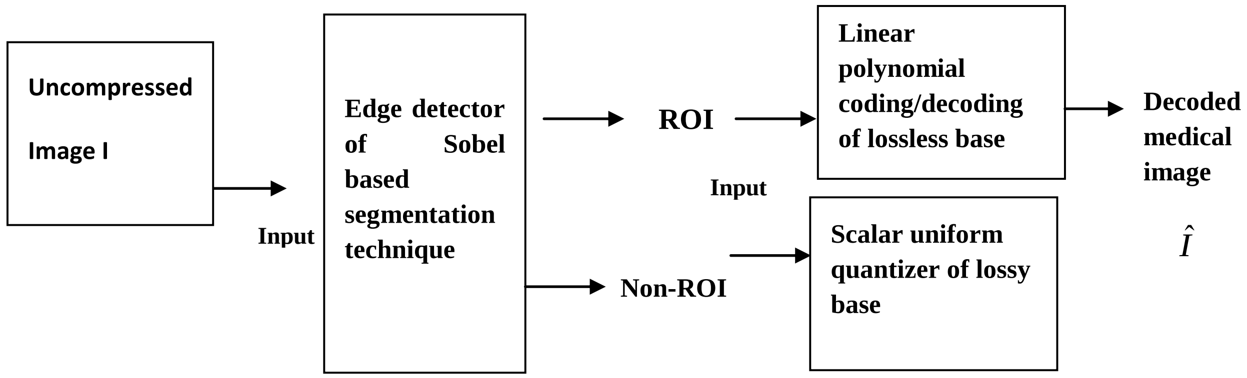


Figure (3): The input/output ROI and polynomial coding techniques.

3.2 Medical image compression using Traditional Linear Polynomial Coding with Single ROI on a non- stationary background of Thresholding based Technique

The medical images may sometimes have additional information, may be imposed at the boundary (border) of the image, so a more sophisticated segmentation process is required that efficiently identify the single main ROI and clears up any unnecessary loads that might affect the encoding process performance. The proposed system involves the following steps, and depicted clearly in figure (4).

Step 1: Load the input uncompressed medical gray image *I* of *BMP* format of size *N*×*N*.

Step 2: Apply thresh holding technique of global base, that effective and quickly to isolate foreground objects from the background of two dominate modes, by selecting a global threshold value (T_{hv}), then classifying all the pixels according to this threshold value. Any pixel value > T_{hv} will correspond to the object point or foreground point; otherwise the point corresponds to the background point. It then assigns black pixel values (i.e. zero intensity values) to the background, and white pixel values (of intensity value one) to the object of interest. This results in a binary image *IBin* through the threshholding segmentation process [4].

$$I_{Bin}(x,y)=\begin{cases}1 & \text{if } I(x,y)>T_{hv}\\ 0 & \text{otherwise}\end{cases} \qquad (11)$$

Step 3: Compute the object features or characteristics, based on size, position and orientation, as follows [4]:

$$A=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} I_{Bin}(i,j) \qquad (12)$$

$$\bar{x}=\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} j\cdot I_{Bin}(i,j)}{A} \qquad (13)$$

$$\bar{y}=\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i\cdot I_{Bin}(i,j)}{A}$$

$$m_x = \sqrt{\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(j-\bar{x})^2 \cdot I_{Bin}(i,j)}{A}} \tag{15}$$

$$m_y = \sqrt{\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-\bar{y})^2 \cdot I_{Bin}(i,j)}{A}} \tag{16}$$

Here A represents the size of the object by counting the number of pixels in the foreground, centre of mass represented by $\bar{x}$ and $\bar{y}$ that corresponds to the average (mean) of j and i coordinates of head object, m_x and m_y corresponds to moment of inertia in j and i coordinates of object.

Step 4: Find ROI coordinates of top, bottom, left and right values according the equations below by utilizing the computed features from step above.

$$ROI_{MiddleCol} = I_{Bin}(\bar{y}) \tag{17}$$
$$ROI_{Top} = First(ROI_{MiddleCol}) \tag{18}$$
$$ROI_{Bot} = Last(ROI_{MiddleCol}) - m_y \tag{19}$$

$$ROI_{MiddleRow} = I_{Bin}(\bar{x}) \tag{20}$$
$$ROI_{Lft} = First(ROI_{MiddleRow}) \tag{21}$$
$$ROI_{Rgt} = Last(ROI_{MiddleRow}) - m_x \tag{22}$$

Where *First* and *Last* return the value of the most the first and last indices corresponding to the nonzero entries of $ROI_{MiddleCol}$ and $ROI_{Middlerow}$ respectively.

Step 5: Apply the Polynomial coding technique to the selected ROI lossless (see section 2)

Step 6: Quantize the background region into two level quantization image (binary image of 1 bpp) using the scalar uniform quantizer of lossy base,

Step 7: Encode the compressed image information of ROI and non-ROI, namely the polynomial coefficients and the residual image with zeros of background image.

At the decoder reconstruct the approximated medical image using the same process of adding the ROI and non-ROI compressed regions that discussed in the previous sub-section.

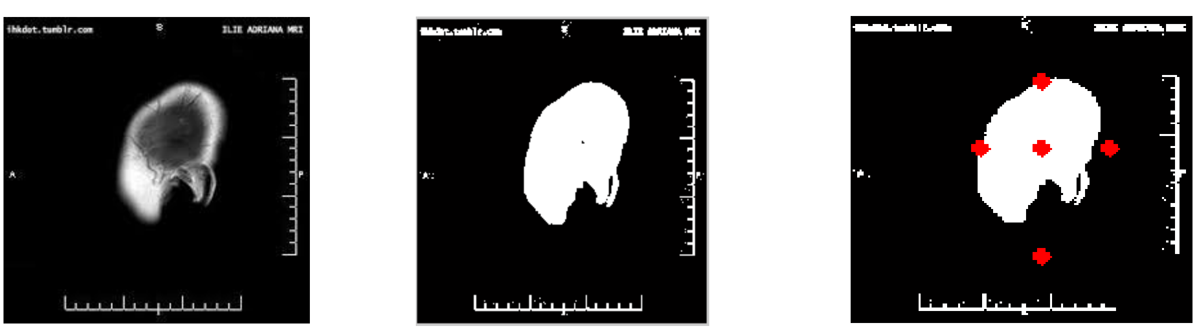
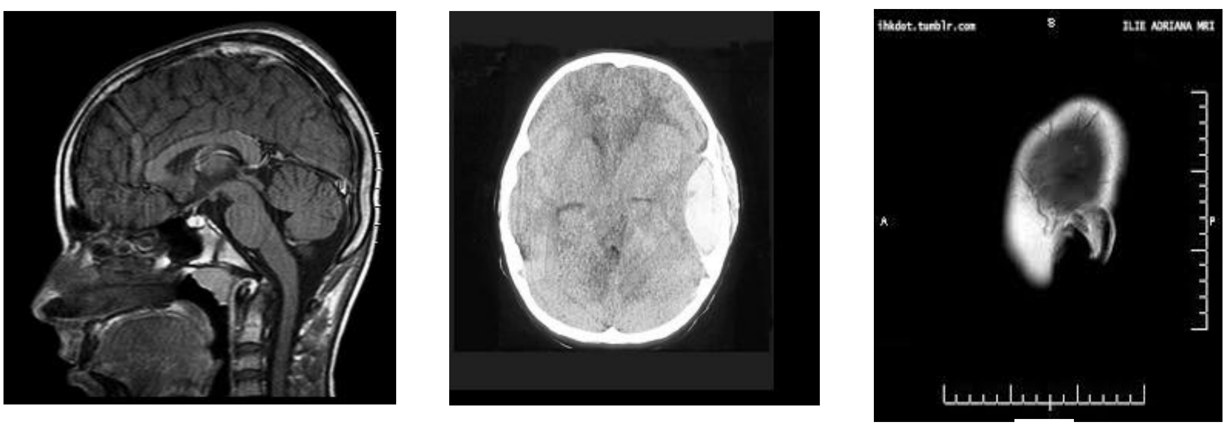


Figure (4): The practical example of the threshold based ROI of feature base technique.

4. Experimental Results

In order to test the performance of the traditional polynomial coding based techniques and comparing it with the proposed methods of ROI base, three standard gray (256 gray levels or 8 bits/pixel) square (256×256) images of varying details are utilized as shown in figure (5), also the compression ratio adopted as the only guide of the system performance, where the compression ratio is the ratio of the original size to the compressed size, in spite of its hybrid nature between lossless and lossy techniques, but actually no degradation occurred, due to preserving all the image information perfectly.



a

Fig. (5): The three tested images of size 256×256, grayscale images, (a) Medical, (b) Medical2, and (c) Medical3

The results shown in tables (1, 2 and 3) illustrate the comparison between the traditional polynomial using block size of *4x4* and proposed techniques, where the three tested images exploited in the first tables of traditional base, while the others tables of ROI base use the images according to the implemented technique.

Table (1): Linear polynomial coding performance using the three tested medical images.

Tested medical images	Linear Poly. Coding
	Compression Ratio

Medical1	**2.4206**
Medical 2	**2.8678**
Medical 3	**4.5410**

The linear polynomial coding characterized by their simplicity and limited redundancy removal in lossless case, since all the blocks use the same number of coefficients regardless of its characteristics while ROI or non-ROI.

Table (2): Linear polynomial coding performance with Single ROI on a stationary background of Edge based Technique using the first two tested medical images.

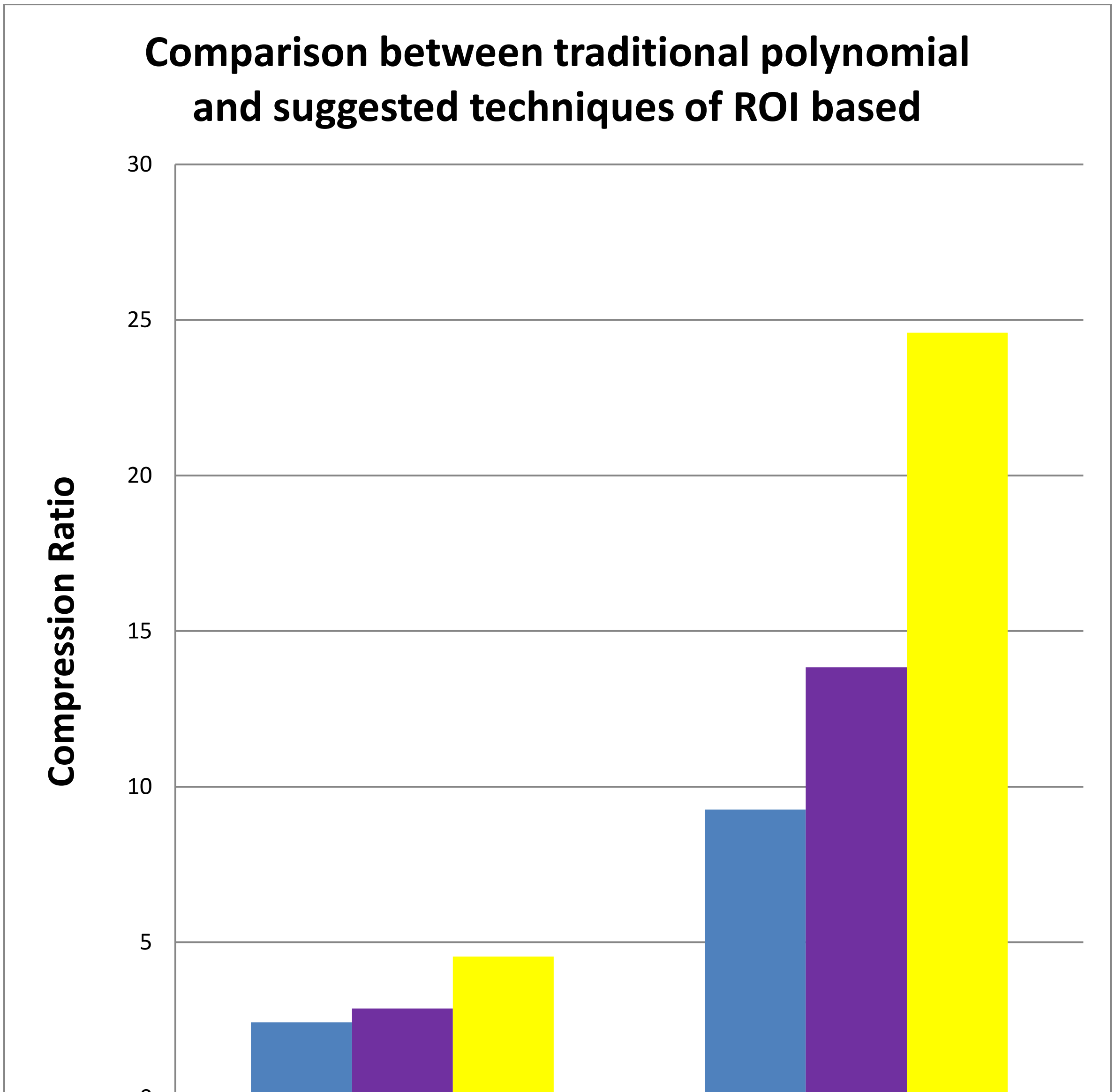
Tested medical images	**ROI Linear Poly. Coding of edge based**
	Compression Ratio
Medical1	**9.2591**
Medical 2	**13.8320**

The results clearly showed that first proposed technique of ROI of edge base improved by (more 2 times) on average compared to the traditional linear, namely improved more than twice on average compared to the traditional linear polynomial coding, that due to efficient utilization to ROI base of stationary black background.

Table (3): Linear polynomial coding performance with Single ROI on a non- stationary background of thresholding based Technique using the third tested medical images.

Tested medical images	**ROI Linear Poly. Coding of threshold based**
	Compression Ratio
Medical3	**24.5872**

The results shown above are promising in terms of the higher compression gain achieved with preserving image quality. The main reason of the improving the compression performance here more than the first proposed technique due to less dominating ROI compared to the first two images, at the same time have large background of binary values that encoded efficiently.
Lastly, as a spatial technique base the results vary according to image details or characteristics, where for a low image details, more compression ratio can be achieved compared to high image characteristic. Figure (6) demonstrates the performance of the traditional polynomial coding and the proposed techniques of ROI base of the tested images.



	1 Traditional Polynomial results	2 Proposed System Results
Medical1	2.4206	9.2591
Medical2	2.8678	13.832
Medical3	4.541	24.5872

Figure (6): The performance of the traditional polynomial coding and the proposed techniques of ROI base of the tested images

5. Conclusions

1-linear polynomial coding is a simple spatial technique that represents the image values using the resident & coefficients alternative from pixel values representation.

2-The ROI of stationary background utilized the edge based to improve their performance by two times on average.

3-The ROI of non-stationary background more complex to implement with higher performance.

6. References

1- G. Al-Khafaji. and H. Al-Mahmood (2013). Lossless Compression of Medical Images using Multiresolution Polynomial Approximation Model. International Journal of Computer Applications, 76(3),38-42.
2- S.Burak, C.Tomasi, B.Girod and C.Beaulieu (2001). Medical Images compression based on ROI with application to colon CT image. Stanford University, in 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Istanbul, Turkey.
3- M. Mohammed and G. Al-Khafaji. (2013). Applied Minimized Matrix Size Algorithm on the Transformed Images by DCT and DWT used for Image Compression. International Journal of Computer Applications, 70(15), 33-40.
4- G. Al-Khafaji (2012). Intra and Inter Frame Compression for Video Streaming. Ph.D. Thesis, Exeter University, UK.
5- S. Dhyaa. (2013). Medical Image Compression. Diploma, Dissertation, University of Baghdad, Collage of Science.
6- G. Al-Khafaji. 2014. Wavelet Transform and Polynomial Approximation Model for Lossless Medical Image Compression. International Journal of Advanced Research in Computer Science and Software Engineering. 4(3), 584-587.
7- G. Al-Khafaji and H. Noori. 2016. Bit-Plane Slicing Autoregressive Modeling for Medical Image Compression. Iraqi Journal of Science, 57(3C), 2318-2323.
8- N.Ghanim (2017). Medical Image Compression using Hybrid Technique of Wavelet Transform and Seed Selected Predictive Method, Diploma dissertation, University of Baghdad, Collage of Science.
9-A.Valdes and M.Trujillo (2013).Medical Image Compression Based on Region of Interest and Data Elimination,Multimedia and Vision Laboratory School of Computer Science and Systems Engineering, Universidad del Valle Cali, Colombia.
10- G. Al-Khafaji.and L.Gorge (2013). Fast Lossless Compression of Medical Images based on Polynomial. International Journal of Computer Applications, 70(15), 28-32.
11- G. Al-Khafaji and Hazim Al-K, (2014). Medical Image Compression using Wavelet Quadrants of Polynomial Prediction Coding & Bit Plane Slicing. International Journal of Advanced Research in Computer Science and Software Engineering, 4(6), 32-36.
12- G.Al-Khafaji and MA.Rajab,(2016). Lossless and Lossy Polynomial Image Compression. IOSR Journal of Computer Engineering (ISO-JCE), 18(4), 56-62
13- A. Abdullah (2018). Hierarchal Polynomial Coding of Grayscale Lossless Image Compression. Diploma Dissertation, University of Baghdad, Collage of Science.
14- L.Sureshkumar and S.kumar (2013) .Applied Intelligent Compression of Medical Images Based on Multi Roi. International Journal of emerging technology and advanced engineering ,3 (1),490-493.

15- M.Mary and P.Chitra (2018). Region of Interest Based Compression of Medical Image Using Vector Quantizer. International Journal of Pure and Applied Mathematics .118 (18), 3059-3067.
16- P.Jangbari and D.Patel (2016) .applied Review on Region of Interest Coding Techniques for Medical Image Compression. International Journal of Computer Applications,134 (10) ,1-5.
17- D.Yee , S.Soltaninejad ,D.Hazarika , G.Mbuyi , R.Barnwal and A.Basu (2017) applied Medical Image Compression based on Region of Interest using Better Portable Graphics (BPG) IEEE International Conference on Systems,34(6),216-221
18- R.Al-Timimi. (2015). Intra Frame Compression Using Adaptive Polynomial Coding. MSc. Thesis, Baghdad University, Collage of Science.

19- G., Al-Khafaji. and R., Yahyaa. 2017. Lossy Image Compression Using Wavelet Transform, Polynomial Prediction and Block Truncation Coding. IOSR Journal of Computer Engineering (IOSR-JCE), 19(4),34-38
20- G., Al-Khafaji,. and S., Amer. 2017. The Use of First Order Polynomial with Double Scalar Quantization for Image Compression. International Journal of Engineering Research and Advanced Technology, 3(6), 32-42.
21- G., Al-Khafaji., S., Fadhil.2017. Image Compression based on Fixed Predictor Multiresolution Thresholding of Linear Polynomial Nearlossless Techniques. Journal of AL-Qadisiyah for computer science and mathematics, 9(2), 35-44.
22- G., Al-Khafaji, and M., A.2018. Fixed Predictor Polynomial Coding for Image Compression. International Journal of Engineering Trends and Technology (IJETT), 61(3), 182-189.