Research Article

Adaptive 1-D Polynomial Coding of C621 Base for Image Compression

Samara S. AL-Hadithy [a], Dr. Ghadah K. AL-Khafaji [b], Dr. Mohammed M. Siddeq [c]

[a] Post graduate Student, Dept. of Computer Science, College of Science, University of Baghdad, IRAQ
[b]Assistant Professor of Computer Science, College of Science, University of Baghdad, IRAQ
[c] Assistant Professor of Engineering Dept., Technical College/Kirkuk, Northern Technical University, IRAQ

Abstract: : The optimal solution to the difficult issues associated with bytes consumption of digital images is to utilize image compression techniques that essentially based on exploiting redundancy(s) efficiently to minimize image size for storage requirements and /or fast transmitted. 1-D polynomial coding is a simple form of the common 2D- polynomial coding that based on modeling spatial image block information using the 1-D nature, which implicitly diminished the extra coefficients of deterministic part and leads to improved compression performance. In this paper, Adaptive 1-D Polynomial Coding for grayscale image compression is proposed with adopting a new compress scheme of six to one data (C621) base for probabilistic part (residual image) effectively, The experimental results tested on six standard gray square images of medical and natural bases, the results showed elegant performance in terms of CR and PSNR compared to the traditional 1-D coding techniques and the well-known standard JPEG, that the compression ratio increase more than three times compared to the traditional 1-D and with higher quality compared to JPEG for the images converged to the same compression performance.

Keywords: Image Compression, Polynomial Coding, JPEG, C621, Search Space Table

1. Introduction

Today, the digital reteam facilities communicate each other cheaply; where image is the core and extensively used, as well as image, convey the information easily and give quickly understanding than the text, which correctly approved the adage that said “A picture is worth a thousand words” (Fisher.Y.1994), but unfortunately comes with huge byte consumptions since its made of thousands and thousands of bits, where image compression become urgently required to exploits the space (storage) and/or speed of data transmission, that implicitly means save cost and time (Abdullah & Ghadah 2021).

Image compression works by packing the image information properly and/or losing data redundancy according to the type of compression that generally categorized (classified) the techniques into lossless and lossy, where lossless base also referred as error free or information preserving that characterized by low compression ratio due to utilizing the statistical redundancy alone (i.e., coding and spatial) and used in military, medical, satellite images, on the other hand lossy base that characterized by high compression ratio due to utilizing the both psycho-visual along the statistical redundancies and used in daily media application including TV, video film, the internet, (Hawraa.B.2019)(Erdal & Ergüzen 2019) for general information on the image compression see (Ismael & Rasha 2017),(Abeer.J. et al.,2018),(Abdulrahman & Abdulrahman 2019). Image compression systems have become an increasingly intensive and important research area, where a huge amount of work had been done to improve the system performance, with coding techniques such as, block truncation, predictive coding, bit plane slicing, vector quantization, and fractal, also reviews of lossless and lossy techniques can be found in (Abeer.J. et al.,2018), (Bhaskara.R. et al., 2013),(Ghadah & Shaymaa 2017),(Boopathiraja.S. et al.,2018),(Jianyu.L. 2019),(Osama.F. et al.,2020).

One of efficient spatial removal techniques is polynomial coding, which is simply a modelling scheme of Taylor series base, where the first order modelling scheme corresponds to linear model, while the higher order modelling scheme (2^{nd} and higher) corresponds to non-linear model, the main distinction between the models lies in the effectively number of coefficients utilized that affects the compression ratio, quality, and complexity (Ghadah & Maha 2016). A large effort had been done to improve the performance of traditional polynomial techniques of 2D base, with tools such as transform coding, hierarchal scheme, quantization, for example (Ghadah & Loay 2013),(Rasha. Al-T. 2015),(Ghadah & Noor 2016),(Ghadah & Sara 2017),(Ghadah & Marwa 2018),(Ghadah. Al-K. 2018),(Ghadah.Al-K. et al.,2019),(Ola.K.2020). Ghadah and Loay (Ghadah &Loay 2021) in 2021adopted anew 1D polynomial scheme of less polynomial coefficients and computation that enhanced the compression performances.

The Minimize Matrix-Size Algorithm technique suggested by Siddeq since 2010 (Mohammed.S. 2010), to compress every three data to single floating point value. Then the Matrix Minimization Algorithm has been developed in Sheffield Hallam University by Siddeq and Rodrigues since 2014 (Mohammed & Marcos 2014) to compress every three data to an integer value, these compressed values can also be used to provide encryption, security or digital right management by preventing unauthorized decompression of image data[25]. The decompression/decryption algorithm based on Sequential Search Algorithm (SS-Algorithm) adopted by Siddeq(Mohammed.S. 2010) to recover original data. On the other hand, the disadvantage of SS-Algorithm takes more time for decoding (time complexity $o(n^2)$) (Mohammed.S. 2010), (Mohammed & Marcos

2014),(Mohammed &Marcos 2015). Since 2015 Siddeq and Rodrigues developed decoding algorithm by using Binary Search Algorithm for fast decoding algorithm, which based on compute all the output probability (Mohammed &Marcos 2015),(Knuth.D. 1997),(Mohammed & Marcos 2016). The disadvantage was time consuming to compute all the output probability.

This paper is concerned with introducing a modified scheme of six to one data (C621) compression along the one-dimensional polynomial coding of highly effective performance of compression ratio and quality. The paper is organized as follows: Section 2 reviews the related works, Section 3 discusses the suggested compression system in detail; the following sections are concerned with the tested results and finally the conclusion with the work limitations.

2. Literature Review

Polynomial coding is a modelling techniques, based on the prediction (deterministic part) and differentiation (probabilistic part). This technique distinguished by their simplicity, symmetry of encoder and decoder, and efficiency as a spatial base technique. (Ghadah.Al-K. et al.,2019). Mostly work had been done investigates and improves the 2D polynomial techniques, due to the simplicity representation of modelling information using the fixed block size of square nature *(nxn)*. A Review of polynomial compression techniques can be found in (Samara & Ghadah 2021), here we review work related to coefficients, residual quantization, and hierarchal scheme, such as: **Ghadah and Loay (2013)**, utilized variable coefficients depending on the characteristics of the block, where for smooth blocks only one coefficient (a_0) is used, and three coefficients (a_0,a_1,a_2) are used for the non-smooth (edged) blocks, this lossless system adopted for compressing medical gray images, with compression ratio between (6-8). **Ghadah and Sarah (2017)**, used the multiple description scalar quantizer (MDSC) to effectively quantize the residual image, where the sum of the two dequantized residual images is applied to the predicted image to recreate the original image in a similar or different manner. This lossy compression system packed gray images, with compression ratio between (4-8), and PSNR between (36-38). **Ghadah and Murooj (2018)**, Adopted selective predictor, where more than one predictor is used depending on the details of the image, where a choice is made between them, depending on the error between (residual) the neighbors, efficiently remove redundancy, The compression ratio of lossy gray system was seven times more than that of the traditional one, with PSNR between (38-39). Lastly **Ghadah et al. (2019)**, exploited other way of hierarchal decomposition of even/odd scheme, here adopted for image, coefficients and residual. The test results of lossless base for medical and gray natural images, showed higher compression ratio that vary between 8.3 to 10.2 according to image details (characteristics).

Also, we have to mention that first work related to 1D polynomial coding suggested by **Ghadah and Loay (2021)**, where the scheme is improved by exploiting one-dimensional model of the deterministic part that leads to negligible in terms of bytes, as well as adopted non-linear quantization technique of the residual probabilistic part, tested on natural and medical gray images, with block size 4×4 , using different quantization steps (Qs) of lossy base ,used Qs=4,8,16,32 ,the compression ratio between (2.1-2.7), (2-4), (4-5), (5-8) respectively and PSNR between (50-55), (47-53), (38-43), (35-38) respectively.

3. The Proposed Compression System

This section investigates the use of mixing techniques of 1D polynomial and C621 to compress gray scale lossily efficiently; the following steps discuss the proposed system in details, and also figure (1) shows the system layout obviously.

Step1: Read the original gray image *F* (8 bits/pixel) of size *N*×*N* of *BMP* format.

Step2: A fixed partition scheme is required to estimate the coefficients of the deterministic part, which entails dividing the image *F* into square fixed blocks (n×n) F_{2D} of size $(N/n)^2$, after that represent each segmented 2D block from F_{2D} into 1D F_{1D} each of size ($1\times n^2$) and assigning coefficients to each block as in step 3, for example for *F* of size *256×256*, 2D block of size *4×4*, that converted into *1×16*, the F_{1D} is of size*4096×16* blocks.

Step3: Use one-dimensional linear polynomial coding techniques of first order Taylor series model to estimate the coefficients (deterministic part) according to equations bellow (Ghadah & Loay 2021).

$$a_0 = \frac{1}{n^2}\sum_{i=0}^{n^2-1} F_{1D}\ (i) \quad \dots\dots\dots\dots\dots\dots (1)$$

Where a_0 coefficient corresponds to the mean (average) of each 1D block,

$$a_1 = \frac{\sum_{i=0}^{n^2-1} F_{1D}\ (i)(i-x_c)}{\sum_{i=0}^{n^2-1}(i-x_c)^2}\ \dots\dots\dots\dots....(2)$$

$$x_c = \frac{n^2-1}{2}\qquad \dots\dots\dots\dots\dots\dots\dots..\dots...(3)$$

The a_1 coefficients represent the first order derivative (moments), while (i-x_c) are known function variables that calculate the distance between pixel coordinates and the block center (x_c), and n^2 is the block size.

Step4: Encode the coefficients losslessly using the Huffman coding of probability base techniques

Step5: Create the predicted image$\tilde{F}_{1D}$ using the estimated coefficients of deterministic part, (Ghadah &Loay 2021) such as:

$$\tilde{F}_{1D} = a_0 + a_1(i - x_c)\ \dots\dots\dots.\dots\dots\dots(4)$$

Step6: Find the residual Res (prediction error) that correspond to Probabilistic part, (Ghadah &Loay 2021] such as:

$$Res = F_{1D} - \tilde{F}_{1D}\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(5)$$

Step7: Applied scalar uniform quantization/dequantization to the Res from step above, using quantization step (QSRes) of lossy base, (Rasha.Al-T. 2015)

$$\text{ResQ} = \text{round}\ (\frac{\text{Res}}{\text{QSRes}})\ \dots\dots.\dots\dots.\dots\dots(6)$$

$$\text{ResDQ} = \text{ResQ} \times\ \text{QSRes}\ \dots..\dots..\dots\dots(7)$$

Where ResQ, $ResDQ$ quantized/dequantized residual images

Step8: Encode residual dequantized residual image $ResDQ$ using a new suggested technique which called C621, that composed of the following sub-steps bellow:

8.1) Generate five floating number keys (*K1*,*K2*,*K3*,*K4*,*K5*) randomly using Matlap programing Language, with range limited between (*0*) to (*1*).

8.2) Create the primary level (PL) using the first three keys (*K1*,*K2*,*K3*) with the first three data residual (d) and multiply each one by the first, second and third keys consecutively and after sum over the result, according to the equation bellow .

$$E(i) = K1 \times d(m) + K2 \times d(m+1) + K3 \times d(m+2)\ \dots\dots\dots(8)$$

Where *E(i)* is the encryption result of summation of triple data and keys , *m* is location of data *d* of $ResDQ$, *i* is the location of each floating point value.

8.3) Create the second level (SL) that sum each twins of the primary level (E_1,E_2,E_3,E_4 ….E_t) after multiply by *K4* and *K5* respectively ,such as:

$$C(j) = K4 \times E(p) + K5 \times E(p+1)\ \dots\dots(9)$$

Where *C(j)* is the compression after second level (SL) ,*p* point to location of *E* , *j* is the location of each floating point value. Figure (2) shows an illustrative example of the steps above, with computing probabilities of compressed data that referred as probability of search space. The size of the Search Space Table based on the size of residual matrix, whereas number of 6 data repetitive and infrequent data in the residual matrix, then written in the Search Space Table.

8.4) Encode/decode the Search Space table and *C* (SL) losslessly using the mixed encoder of use Huffman and LZW coding techniques. (Rubaiyat.H. 2011).

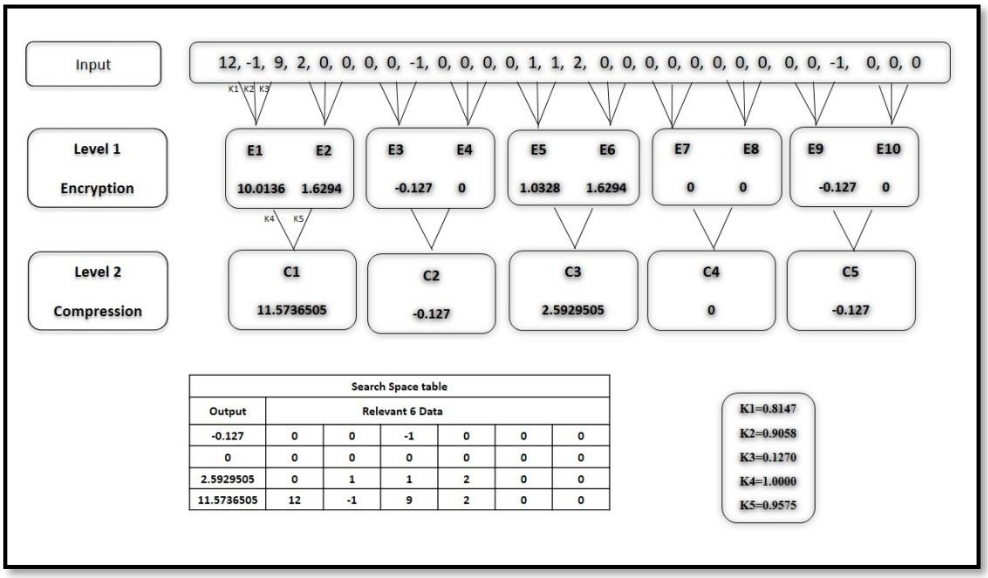


Figure.2 Example of C621 levels.

8.5) reconstruct the decoded residual image of C621base Res_{C621}using the binary search algorithm, to speed up the decompression process. The decompression algorithm start with binary search algorithm, which used to find compressed data inside the Search Space Table as shown in the Figure (3) bellow:

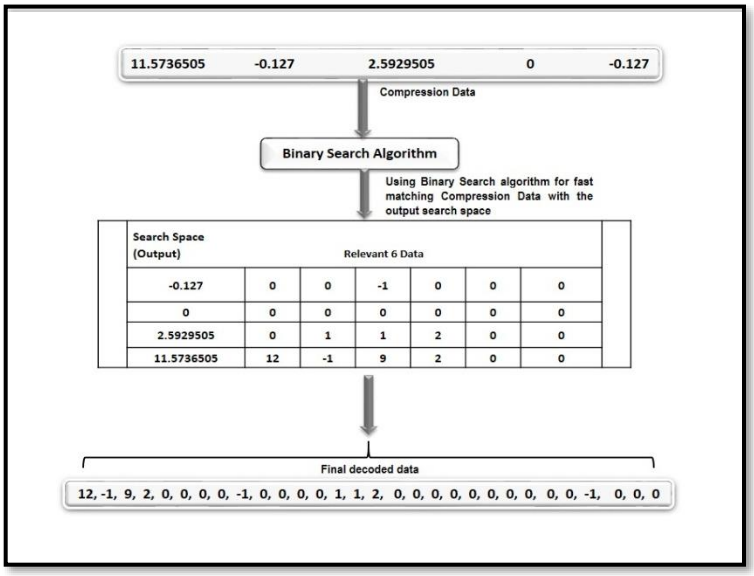


Figure.3 Example to decoding of

In the proposed system the binary search usually requires sorting the Search Space table in ascending order based on the output. Each compressed data item is compared to the middle value in the output column for Search Space table. If one of values is match, the relevant 6 data items that are returned. (Knuth.D. 1997). Alternatively, if the data value is less than the middle of output column, the algorithm is then repeated on the sub-array to the top of the middle output, or on the sub-array to the down if the value is greater (Knuth.D. 1997). Since the table was previously constructed at compression stage and contained one component of each original data, the probability of a "un-matched" does not exist (Mohammed & Marcos 2016).

Step9: Reconstruct the approximated decoded image ($\hat{F}_{1D}$) of two parts according to equation (11), the deterministic part which is predicted image of 1D base ($\widetilde{F}_{1D}$) (see Step5) and the Probabilistic part which is decoded Residual image after performing the C621 (Res_{C621}), then re-represented $\hat{F}_{1D}$ or converted into $\hat{F}$ of 2D base.

$$\hat{F}_{1D} = \tilde{F}_{1D} + Res_{C621} \dots\dots\dots (10)$$

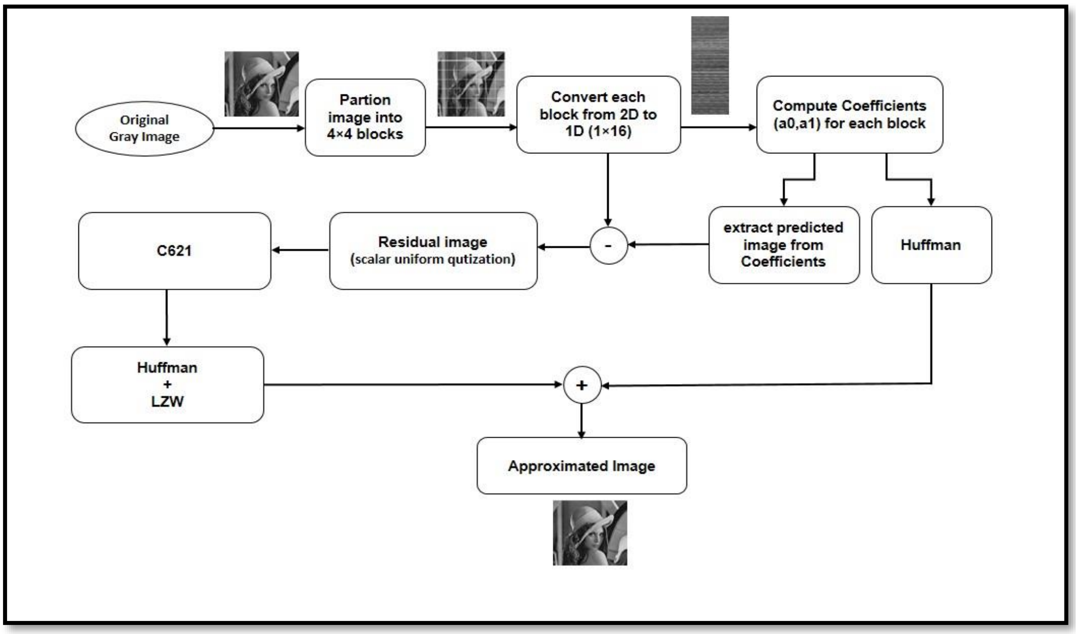


Figure.1 proposed system

4.Results and Discussion

Mainly two well-known measures were used to evaluate the performance of the proposed compression system: compression ratio (CR) and where CR is defined as the ratio of the size of original image and size of the compressed bits stream. The objective fidelity criteria of Peak signal-to-noise ratio (PSNR), where PSNR is defined as the ratio between the maximum values of the signal as measured by the magnitude of the noise that affects the signal, according to equations (11-12). As shown in Figure (4), mainly two image types were tested: natural and medical. All of the images tested are grayscale (8bits/pixel), square (256×256) images of65536 bytes, and using the block size of 4×4. Proposed compression system is implemented by using MATLAB application version R2012b programming language, on a laptop computer of Intel ® Core ™ i7- 8565U CPU @ 1.80GHz processor , RAM 8.00 and Windows 10 pro Operating system(64 bit).

$$CR = \frac{Original\ Image(Size\ in\ Bytes)}{Compressed\ Image\ (Size\ in\ Bytes)} \dots\dots\dots.(11)$$

$$PSNR(F,\hat{F}) = 10log_{10}\left(\frac{(255)^2}{\frac{1}{N\times N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}[\hat{F}(x,y) - F(x,y)]}\right)\dots\dots(12)$$

Where *F* represents the original image (uncompressed image) and $\hat{F}$ represents decoded compressed image.

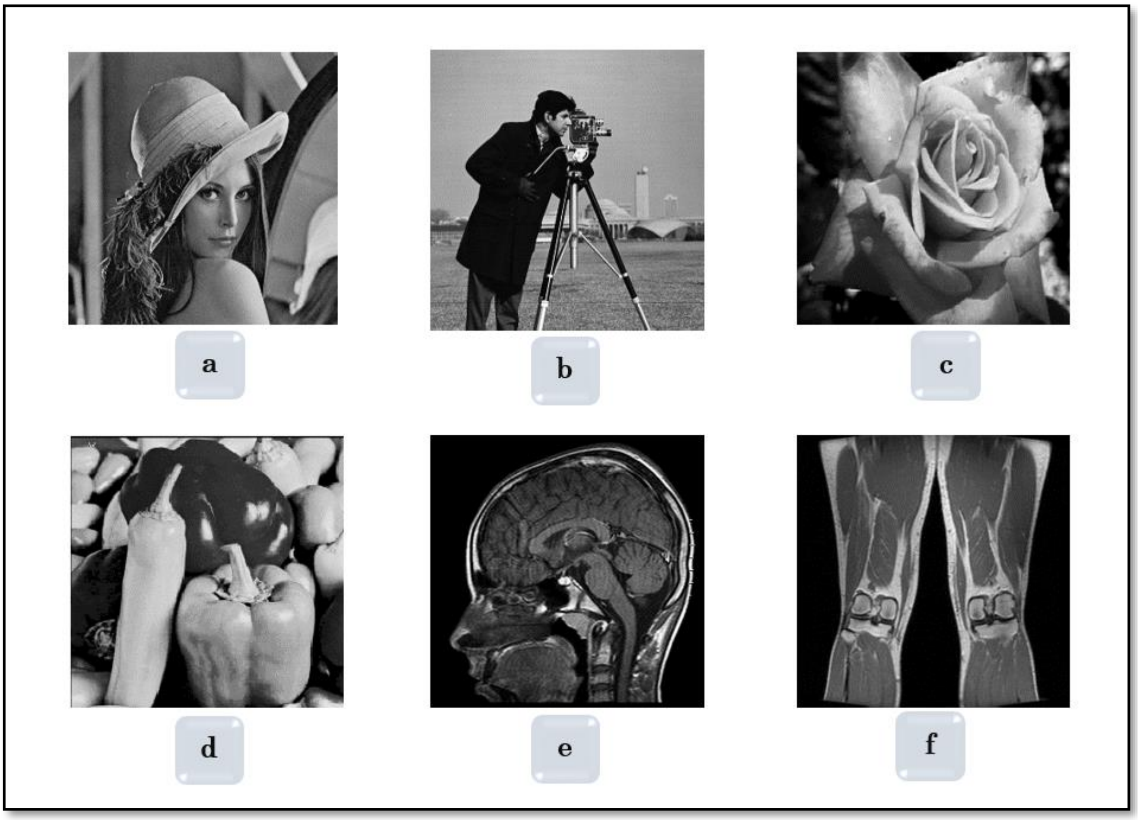


Figure.4 The natural and medical testing image, where a) Lena b)Camera_man c)Rose d)Pepper e)Brain and f)Knee

As mentioned previously, the polynomial coding composed of two parts of deterministic and probabilistic bases respectively, so to find the size of compressed polynomial information that implies the size in bytes of encoded losslessly coefficients (a_0,a_1) using the Huffman coding of probability base along the C621 encoded residual information lossily of mixing techniques of LZW and Huffman coding along the overhead information that corresponds to block size, quantization step and key, that represented such as:

$$\boldsymbol{PolyComp_{InBytes}} = [\boldsymbol{sizeofCofficients}(\boldsymbol{a_0}, \boldsymbol{a_1}) + \boldsymbol{SizeofC621_{Residual}} + \boldsymbol{sizeofoverhead}] \ldots\ldots..(13)$$

Where $PolyComp_{InBytes}$ corresponds to the total required bytes to represents the compressed image information.

We have to mention here that the range of quantization/dequantization step *QSRes* of residual image was selected to be between 1 and 10 of uniformly base, Table (1) shows the performance of the proposed system for the size tested images in terms of *CR* and *PSNR* using *QSRes* of values equals to 1, 2, 4, and 10 respectively.

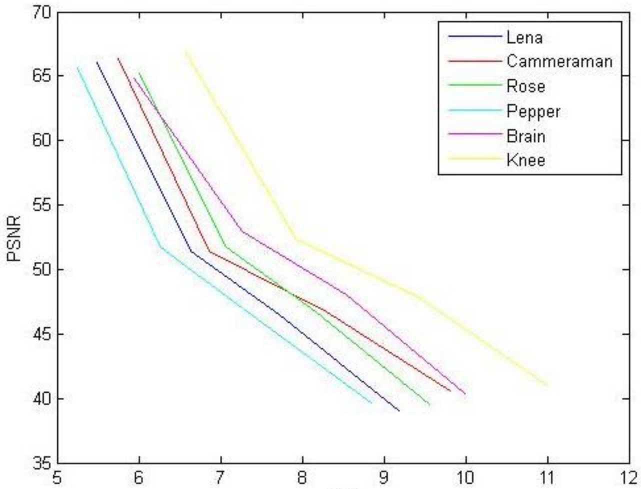


Figure.5 The performance of the proposed system, CR Versus PSNR for the tested images using QRes =1,2,4,and 10.

Table.1. The proposed system performance for tested images

Tested Images	**Performance of the proposed system using block size of 4x4 and four cases of uniform quantization process of C621 base**											
	QSRes=1			**QSRes=2**			**QSRes=4**			**QSRes=10**		
	Poly. Comp. Size in Bytes	CR	PSNR $(F,\hat{F})$	Poly. Comp. Size in Bytes	CR	PSNR $(F,\hat{F})$	Poly. Comp Size in Bytes	CR	PSNR $(F,\hat{F})$	Poly. Comp Size in Bytes	CR	PSNR $(F,\hat{F})$
Lena	11920	5.4980	66.0791	9878	6.6345	51.4122	8494	7.7156	46.4838	7140	9.1787	39.0500
Camera man	11406	5.7457	66.3637	9560	6.8552	51.4210	7890	8.3062	46.7256	6680	9.8108	40.5848
Rose	10916	6.0037	65.2160	9260	7.0773	51.7426	8024	8.1675	46.7519	6856	9.5589	39.5382
Pepper	12502	5.2420	65.6719	10464	6.2630	51.7235	8946	7.3257	46.7678	7404	8.8514	39.6739
Brain	11036	5.9384	64.8412	9020	7.2656	52.9702	7670	8.5445	48.0162	6562	9.9872	40.4232
Knee	9960	6.5799	66.8453	8274	7.9207	52.3433	6946	9.4351	47.8028	5952	11.0108	40.9970

It is obvious that the *CR* and *PSNR* directly affected the selected values of residual quantization step *QSRes*, with inversely relation between these measure, where high *PSNR* values indicate high image quality with low *CR*, and vice versa, Figure (5) illustrates the performance of the proposed system for the tested images, also Figure (6) shows the original and compressed tested images of high quality where *QSRes* value equals 2.

Test ed	***Original image***	***Higher image quality***	***Te sted***	***Original image***	***Higher image quality***

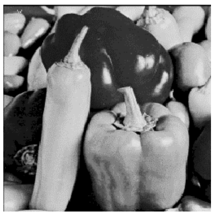
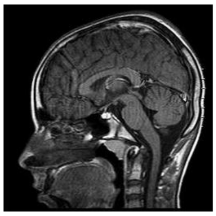
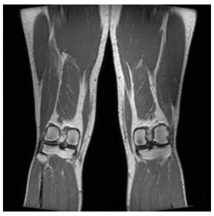
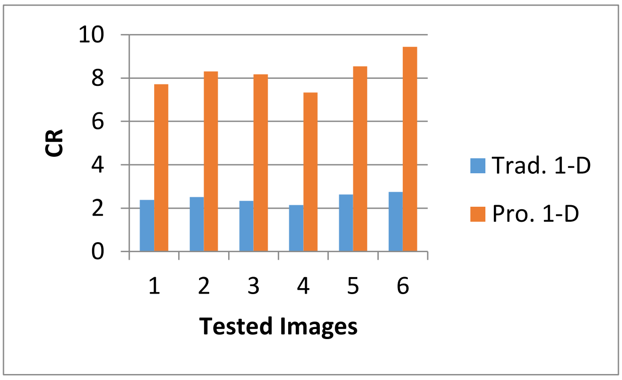
image			***image***		
Lena		 CR=6.6345 PSNR=51.4122	***Pepper***		 CR=6.2630 PSNR=51.7235
Camera-man		 CR=6.8552 PSNR=51.4210	***Brain***		 CR=7.2656 PSNR=52.9702
Rose		 CR=7.0773 PSNR=51.7426	***Knee***		 CR=7.9207 PSNR=52.3433

Figure.6 Examples of original images and and compressed images of high quality of using QRes =2.

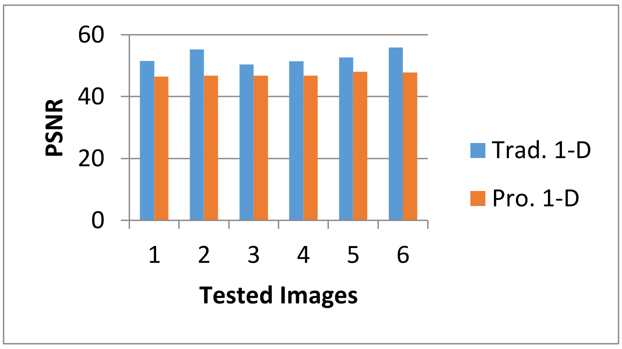
Lastly, the comparison performance with first paper of 1-D base (Ghadah &Loay 2021) along the well-known standard JPEG with *QSRes*=4 adopted in the proposed system as well as for (Ghadah &Loay 2021), where results shown in tables (2) and (3) and figures (7-8) respectively.

Table.2. Comparison performance with 1-D base (Ghadah &Loay 2021) using *QSRes*=4

Tested Images	**1-D base [22]**		**Proposed system**	
	QSRes=4		**QSRes=4**	
	CR	**PSNR $(F,\hat{F})$**	**CR**	**PSNR $(F,\hat{F})$**
Lena	2.3788	51.4905	7.7156	46.4838
Cameraman	2.5149	55.2948	8.3062	46.7256
Rose	2.3344	50.4196	8.1675	46.7519
Pepper	2.1422	51.4190	7.3257	46.7678
Brain	2.6249	52.6582	8.5445	48.0162
Knee	2.7488	55.9185	9.4351	47.8028



a



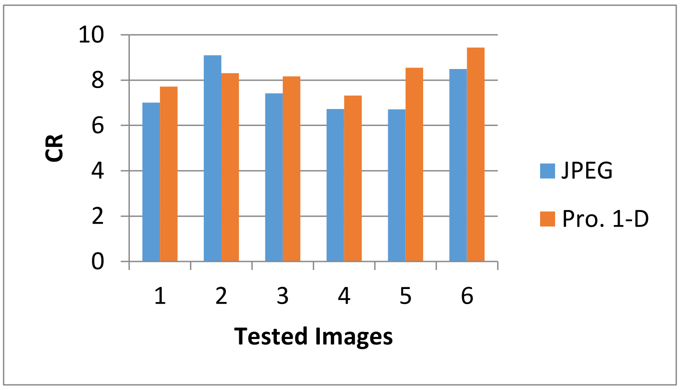
b

Figure.7 The comparison performance between the traditional 1D polynomial and the proposed system in terms of a) CR and b) PSNR for tested images.

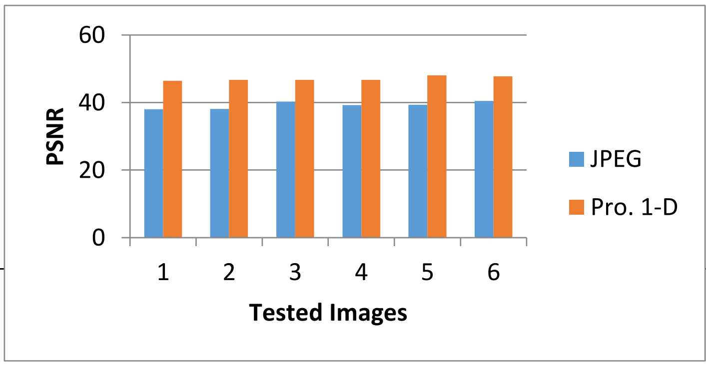
Clearly, from the above results, the proposed system shows superiority in CR compared with (Ghadah & Loay 2021) but with small differences quality due to the non-uniformity nature of quantization step that adopted by (Ghadah &Loay 2021), on the other hand JPEG standard techniques converge to the proposed system in CR, but with higher quality of the proposed techniques of spatial base utilization.

Table.3. Comparison performance with JPEG and the proposed 1-D base using *QSRes*=4

Tested Images	**JPEG**		**Proposed system**	
			QSRes=4	
	CR	**PSNR** $(F,\hat{F})$	**CR**	**PSNR** $(F,\hat{F})$
Lena	7.0099	38.05	7.7156	46.4838
Cameraman	9.0921	38.14	8.3062	46.7256
Rose	7.4160	40.25	8.1675	46.7519
Pepper	6.7299	39.26	7.3257	46.7678
Brain	6.7161	39.38	8.5445	48.0162
Knee	8.4891	40.47	9.4351	47.8028



a



b

Figure.8 The comparison performance between the standard JPEG and the proposed system in terms of a) CR and b) PSNR for tested images**.**

5.Conclusions

- The tested results directly affected by the image features (characteristics) and the quantization process of uniformity base.
- The use of 1-D polynomial coding and C621 can be utilized to compress images efficiently of high compression ratio and performances
- The C621 Lossless data compressed used for encryption and secure unauthorized images. Because C621 algorithm based on five different keys also uses space search table, in case if these keys and space search table is lost or damaged the image unrecoverable.

The proposed system still have some limitations to be used as a practical or commercial application, firstly still slow and complex and the control parameters (block size, quantization step, key) needs to be optimized, secondly the simplicity of coefficients of symbol encoder and the restrictions of image gray type and size . Additionally, the decoding C621 uses binary search algorithm based on keys, which is add complexity to our proposed algorithm.

References

1. Fisher, Y. (1994). Fractal Image Compression: Theory and Application. Springier Verlage, New York.
2. Abdullah, A., Ghadah, Al-K. (2021). A Pixel Based Method for Image Compression, Tikrit Journal of Pure Science, 26 (1),113-122.
3. Hawraa, B. (2019). Adaptive Color Image Compression of Polynomial based Techniques Higher Diploma Dissertation, University of Baghdad, Collage of Science, Iraq.
4. Erdal, E., Ergüzen, A. (2019). An Efficient Encoding Algorithm using Local Path on Huffman Encoding Algorithm for Compression. Applied Sciences, 9(4), 782.-800.
5. Ismael, H., Rasha, R. (2017). Suggested hybrid Transform Technique for image compression. Journal of Madent Alelem College, 9 (2),15-27.
6. Abeer, J., Ali, Al-F., Naeem, R. (2018). Image compression Techniques: A Survey in Lossless and Lossy Algorithms. Neurocomputing, 300, 44-69.
7. Abdulrahman, Altu., Abdulrahman, Alro. (2019). A Novel Lossless Image Compression Technique Based on Firefly Optimization Algorithm, Journal of Engneering and Applied Sciences, 14(8), 2642-2647.
8. Bhaskara, R., Hema, S., Kiran, S., Anuradha, T. (2013). A Novel Approach of Lossless Image Compression using Hashing and Huffman Coding, International Journal of Engineering Research & Technology (IJERT), 2(3),1-8, ISSN: 2278-0181.
9. Ghadah, Al-K., Shaymaa, F. (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.
10. Boopathiraja, S., Kalavathi, P., Chokkalingam S. (2018). A hybrid lossless encoding method for compressing multispectral images using LZW and arithmetic coding. International Journal of Computer Science and Engineering, 6 (4), 313–318.

11. Jianyu, L. (2019). A New Perspective on Improving the Lossless Compression Efficiency for Initially Acquired Images, Department of Electronic Engineering, Shantou University, China IEEE Access Journal, 7, 144895- 144906.
12. Osama, F., Aziza, I., Hesham, F., Hamdy, M., Ashraf, A. (2020). Efficient Combination of RSA Cryptography, Lossy, and Lossless Compression Steganography Techniques to Hide Data, 17th International Learning & Technology Conference 2020 (17th L&T Conference), Procedia Computer Science, 182, 5-12.
13. Ghadah, Al-K., Maha, A. (2016). Lossless and Lossy Polynomial Image Compression, IOSR Journal of Computer Engineering (IOSR-JCE), 18(4), 56-62.
14. Ghadah, Al-K., Loay, E. (2013). Fast Lossless Compression of Medical Images based on Polynomial. International Journal of Computer Applications, 70(15), 28-32.
15. Rasha, Al-T. (2015). Intra Frame Compression Using Adaptive Polynomial Coding. MSc. Thesis, University of Baghdad, Collage of Science.
16. Ghadah, Al-K. , Noor, S. (2016). Image Compression based on Adaptive Polynomial Coding of Hard & Soft Thresholding. Iraqi Journal of Science, 57(2B), 1302-1307.
17. Ghadah, Al-K., Sara, A. (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.
18. Ghadah, Al-K., Marwa, B. (2018). Polynomial Color Image Compression. International Journal of Engineering Trends and Technology (IJETT), 61(3), 161-165.
19. Ghadah, Al-K., (2018). Linear Polynomial Coding with Midtread adaptive Quantizer. Iraqi Journal of Science, 59(1), 585-590.
20. Ghadah, Al-K., Abdullah, A., Uhood, Al-H. (2019). Hierarchal Polynomial Coding of Grayscale Lossless Image Compression. International Journal of Computer Science and Mobile Computing, 8(6), 165-171.
21. Ola, K. (2020). Polynomial Color Image Compression using Joint and Different Models. Higher Diploma, University of Baghdad, Collage of Science, Iraq.
22. Ghadah, Al-K., Loay, E. (2021). Grey-Level Image Compression Using 1-D Polynomial and Hybrid Encoding Techniques, Journal of Engineering Science and Technology. Journal of Engineering Science and Technology (in press).
23. Mohammed, S. (2010). JPEG and Sequential Search Algorithm applied on Low-Frequency Sub-Band, Journal of Information and Computing Science, 5(3), 161-240.
24. Mohammed, S., Marcos, A. (2014). A Novel Image Compression Algorithm for high resolution 3D Reconstruction, 3D Research, Sheffield Hallam University Research Archive Springer, 5(7), 17.
25. Mohammed, S., Marcos, A. (2015). Applied sequential-search algorithm for compression-encryption of high-resolution structured light 3D data. In: BLASHKI, Katherine and XIAO, Yingcai, (eds.)MCCSIS : Multi-conference on Computer Science and Information Systems , IADIS Press, 195-202.
26. Mohammed, S., Marcos, A. (2015). A novel 2D image compression algorithm based on two levels DWT and DCT transforms with enhanced minimize-matrix-size algorithm for high resolution structured light 3D surface reconstruction. 3D Research, 6 (3), 26.
27. Knuth, D. (1997). Sorting and Searching: Section 6.2.1: Searching an Ordered Table, The Art of Computer Programming 3 (3rd Ed.), Addison-Wesley, 409–426. ISBN 0-201-89685-0.
28. Mohammed, S., Marcos, A. (2016). Image Data Compression and Decompression Using Minimize Size Matrix Algorithm, Sheffield Hallam University WO 2016/135510 A1.
29. Samara, S., Ghadah, Al-K. (2021). Polynomial Image Compression: A Review. 1st International Conference for Pure Science (ICPS-2021) in College of Science / University of Diyala, Iraq, by AIP Conference Proceeding (ISSN: 0094-243X) (in press).
30. Murooj, A. (2018). Fixed and Selective Predictor Polynomial Coding for Image Compression. Higher Diploma, University of Baghdad, Collage of Science, Iraq.
31. Rubaiyat, H. (2011). Data Compression using Huffman based LZW Encoding Technique. International Journal of Scientific & Engineering Research, 2 (11) 1-7, (ISSN 2229-5518).