

QUANTIZATION MATRIX FOR MEDICAL IMAGE COMPRESSION USING FRAMELET TRANSFORM

Dr. Atheer Alaa Sabri University of Technology Department of Electrical Engineering atheeralaa@yahoo.com Nora Hussam Sultan University of Technology/ Department of Electrical Engineering eng.nhs_2009@yahoo.com

Received: 24 / 11 / 2013

Accepted: 4 / 2 / 2014

Abstract

In this paper, two quantization matrices are proposed that is suitable to compress medical images using framelet transform. Also two algorithms are suggested to compress medical images. One of them is used for grayscale and color medical images while the second is used for grayscale medical images only. It is found that the first proposed quantization matrix is better than the second in terms of Peak Signal to Noise Ratio (**PSNR**). While the second proposed quantization matrix is faster than the first. The work suggested in this paper is compared with wavelet and multiwavelet based algorithms and other previously related works and it is found that the quantization matrices proposed are most suitable for compression medical images with framelet transform and framelet transform is the best compression method for medical images.

Key words: Framelet Transform, Quantization Matrix, Peak Signal to Noise Ratio (PSNR), Compression Ratio (CR), Medical Images and Image Compression.

الطبية باستخدام التحويل الاطاري	مصفوفة التكميم لضغط الصور
نورا حسام سلطان	د. اثير علاء صبري
الجامعة التكنولوجية	الجامعة التكنولوجية
فسنم المهندستة الكهريانية	فسنم الهندسة الكهربانية

الخلاصة

Framelet) يقترح هذا البحث مصفوفتين مناسبتين لضغط الصور الطبية باستخدام التحويل الاطاري (**Framelet**) لتترح هذا البحث مصفوفتين مناسبتين لضغط الصور الطبية. طبقت الخوارزمية الاولى على الصور الطبية الرمادية (**Transform**). حيث تم اقتراح خوارزميتين لضغط الصور الطبية. طبقت الخوارزمية الاولى على الصور الطبية الرمادية (**grayscale**) والملونة (**color**) بينما طبقت الخوارزمية الثانية على الصور الطبية الرمادية (**grayscale**) والملونة (**color**) بينما طبقت الخوارزمية الثانية على الصور الطبية الرمادية فقط. وقد أعطت مصفوفة التكميم المقترحة الاولى افضل نتائج من ناحية جودة الصورة بينما كانت المصفوفة المقترحة الثانية اسرع من الولى وقد تم مقارنة المقترحة الثانية المورة بينما كانت المصفوفة المقترحة الثانية اسرع من الاولى. وقد تم مقارنة العمل المقترح مع تحويل المويجة (**wavelet**) والحافضل فتارح مع الحويل المويجة (**wavelet**) والحافظ وغيرها من الاعمال المتعلقة السابقة. ووجد ان مصفوفة التكميم المقترحة التحميم المقترحة مع الحويل اللولي هي أكثر ملائمة وافضل طبية الرعمال المتعلقة والحافي والحمال المعالية الرعمال المتعلقة ووجد الموردة العمال طبية الرعمال المور الطبية الرعمال المتعلقة اللولى وقد تم مقارنة العمل المقترحة مع التحويل اللولي هي أكثر ملائمة وافضل المورية الصور الطبية. والحمال المتعلقة المويجة (**b** المورية الموركة والموركة والحوال والي المولية الموركة الموركة والموركة والمولي والحمال المتعلقة والمولي والي المولى والحمال المتعلقة المولي المولي العمال الموركة والموركة والمولي المولي من المولية المولي المولي من المولي من المولي والمولي المولي والي المولي والمولي المولي والمولي المولي والمولي المولي المولي والمولي المولي والمولي المولي والمولي المولي والمولي المولي والمولي المولي المولي المولي المولي والمولي والمولي مولية المولي والمولي والمولي المولي الم



1. Introduction

Following the rapid development of information and Communication Technologies, more and more information has to be processed, stored, and transmitted in high speed over networks. The need for data compression and transmission is increasingly becoming a significant topic in all areas of computing and communications. Computing techniques that would considerably reduce the image size that occupies less space and bandwidth for transmission over networks form an active research [Fatima B. Ibrahim,2010].

Image compression plays a critical role in telematics applications and especially in telemedicine as shown in **Figure 1**. Instance, it is necessary that medical images be transmitted so as that reliable, improved and fast medical diagnosis performed by many centers could be facilitated. To this end, image compression is an important research issue. The difficulty, however, in several applications lies on the fact that, while high compression rates are desired, the applicability of the reconstructed images depends on whether some significant characteristics of the original images are preserved after the compression process has been finished [Adina Arthur and V.Saravanan,2012].



Fig. 1 Telemedicine Concept [Adina Arthur and V.Saravanan,2012].

For instance, in medical image compression applications, diagnosis is effective only when compression techniques preserve all the relevant and important image information needed. This is the case with lossless compression techniques. Lossy compression techniques, on the other hand, are more efficient in terms of storage and transmission needs but there is no warranty that they can preserve the characteristics needed in medical image processing and diagnosis. In this latter case, of lossy compression, image characteristics are usually preserved in the coefficients of the domain space in which the original image is transformed. That is, for instance, in the Discrete Wavelet Transform (DWT) based medical image compression, the wavelet coefficients keep all the information needed for reconstructing the medical image [J.Pinto and Jayanand P. Gawande,2012].

Framelet is very similar to wavelets but has some important differences. Framelet has two or more high frequency filter banks, which produces more sub bands in decomposition. This can achieve better time- frequency localization ability in signal processing. Moreover, framelet is more robust [Runhai Jiao and Biying Lin,2010]. In this paper, a new medical image compression algorithm is proposed using framelet transform.



2. Framelet Transform (FLT)

FLT is based on the theory of multi-resolution analysis (MRA) [RitamMisra .et al,2012] and is an extension of wavelet transform in the sense that it is defined in terms of one scaling function given by eq. (1):

$$\phi(t) = \sqrt{2} \sum_{n} h_0(n) \phi(2t - n) \dots \dots eq.(1)$$

and two wavelet functions given by eq. (2):

$$\psi_i(t) = \sqrt{2} \sum_n h_i(n)\phi(2t-n), i = 1, 2 \dots \dots \dots \dots \dots eq. (2)$$

Where $h_t(n)$, i = 0, 1, 2, are the filters that follow Perfect Reconstruction (PR) conditions. This implies that the synthesis filters are time flipped versions of the analysis filters. Only real-valued $h_i(n)$ having finite impulse response (FIR) has been considered to design these filters [**RitamMisra .et al,2012**].

Physically, the system consists of a three channel filter bank as shown in **Figure 2**, for analysis each filter is down-sampled by 2. The synthesis filters are the time flipped version of the analysis filters **[RitamMisra .et al,2012]**



Fig. 2 Physical Arrangement of the Filter Bank [RitamMisra .et al,2012].

3. Quantization Matrix

Quantization is the process of reducing the number of bits needed to represent the transformed coefficients by reducing the precision of those values by dividing each element in the transformed image matrix D by the corresponding element in the quantization matrix, and then rounding to the nearest integer value as illustrated in eq. (3).

$$Ci, j = round \left(\frac{Di, j}{Qi, j}\right) \dots \dots eq. (3)$$

Since

Kufa Journal of Engineering (K.J.E) ISSN 2207-5528 Vol. 5, Issue 2, June, 2014 Printed in Iraq



this process is a many-to-one mapping, it is a lossy process and it is the main source of compression in the encoding path [S.Taubman, et al,2002]. A quantizer can be specified by its input partitions and output levels (also called reproduction points). If the input range is divided into levels of equal spacing, then the quantizer is termed as a uniform quantizer, and if not, it is termed as a non-uniform quantizer [N. Thanoon, et al,2008].

The quantization matrices are studied in this work. These are:

i. Standard matrix (Q_S) in eq. (4) [S.Taubman, et al,2002]:

 $Q_{S} = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$

ii. Quantization matrix in eq. (5) [N. Thanoon, et al,2008].:

 $Q_1 = \frac{a \times r(i+j)}{s} \dots \dots eq. (5)$

where, $\boldsymbol{a} = 1$ or 2,

 $r = [0.1, 0.2, \dots, 5],$

and s = 2, 4, 6, or 8.

iii. Quantization matrix in eq. (6) [M. Siddeq, 2010]:

 $Q_2 = 1 + (i+j) \times R$ eq. (6)

Where the parameter R is computed by selecting maximum coefficient from a 8×8 frequency components and then multiply by ratio=75%.

4. Proposed Work

The suggested work in this paper can be divided as:

i. Proposed Quantization Matrices

a. The first proposed quantization matrix (Q_{α}) in *eq.* (7):

 $Q_a = L + (i + j) \times R(LL) \dots eq. (7)$



The parameters R(LL) and (L) are computed by selecting maximum coefficient from a LL frequency components (Max (LL)) and then multiply by ratio.

Where $R(LL) = Max(LL) \times r_1$,

 $L = \text{Max} (\text{LL}) \times r_2,$

and these ratios $(r_1 and r_2)$ are adjusts from the user to change the image quality and compression ratio.

b. The second proposed quantization matrix (Q_b) in eq. (8):

 $Q_b = L + \frac{(i+j) \times F}{s} \dots \dots eq. (8)$

Where, the parameter L computed by selecting maximum coefficient from a LL frequency components multiplied by ratio (r) such as 0.05, 0.1, 0.5 etc., *factor* (F) = 2, 3, 4, 5, etc. and s = 2, 3, 4, 5, 6, 7, etc... These values are adjusts by the user to change an image quality to obtain better compression ratio.

ii. Proposed Algorithms

a. The First Proposed Compression Algorithm

The block diagram of the first proposed compression algorithm shows in Figure 3.







The main concerns in the proposed system are:

- **1**. Generate LL sub-band by applying FLT on image.
- 2. Apply Quantization matrix on each 8×8 block of the low-frequency sub-band (LL).
- **3.** Before compress an image using coding methods, the image quality must be saved, by Applying inverse quantization matrix for the LL sub-band which is resulted from step (2).
- **4.** The image quality is obtained from the difference between the original image and the reconstructed image.
- 5. Compress the (LL) after quantization process, using RLE and Huffman coding.
- 6. Compress the D-Matrix resulting from step (4), by using Arithmetic Coding.
- 7. To compress D-Matrix, the matrix should be dividing by a value called Q-Value. This value is adjusted by the user to change the image quality to obtain compression ratio. The range of the "Q-Value" between {1...m}, where m represents maximum value in D-Matrix as shown in eq. (9):

Where r_{D} is ratio such as (0.01, 0.02,...0.05, 0.1, 0.2,...0.5, etc.). Then minimized D-Matrix using (Minimize Algorithm [M. Siddeq,2010]) and then compress each row by arithmetic coding.

• Decompression System of Algorithm (1)

The decompression algorithm will be the inverse for the compression algorithm, and the (Sequential Search Algorithm [M. Siddeq,2010]) must be used to construct D-Matrix then add with LL reconstructed to increase the quality as shown in Figure 4.



Fig. 4 Decompression Algorithm (1).



b. The Second Proposed Compression Algorithm

The main reason of using Framelet transform is to reduce an image dimensions, and the high-frequencies coefficients are ignored (i.e. not used in algorithm (1)), this process increases compression ratio. But this will affect on the quality of some images, especially images that do not contain high psychovisual redundancy. Therefore, this algorithm suggests compressing each component to save quality for the medical images.

The block diagram of the proposed algorithm (2) is shown in Figure 5.



Fig. 5 Encoder of Compression Algorithm (2).

The procedure of algorithm (2) can be explained in the following steps:

- 1. The pixels of an image are organized in groups of 16×16 pixels and each group is compressed separately. If the number of image rows or columns is not a multiple of 16, the bottom row and the rightmost column are padded with zeros as many times as necessary.
- 2. A single-stage Framelet transform is then applied on each group of 16×16 pixels to create an 24×24 map of nine frequency

 $bands(LL,LH_1,LH_2,H_1L,H_1H_1,H_1H_2,H_2L,H_2H_1,H_2H_2).$

- Each of the 576 frequency components in a 24 × 24 map are divided by a separate numbers called Quantization matrix, this quantization matrix represented by the equations (7) or (8) and then rounded to an integer.
- 4. Finally, the same procedure of algorithm (1) should be used to obtain the difference matrix between original image and reconstructed image, as shown in Figure 5 then



compress the D-Matrix for adding it's consequentially in decompressed process to save image quality.

• Decompression System of Algorithm (2)

The decompression algorithm represents the inverse for each process in algorithm (2), and the Sequential Search Algorithm [M. Siddeq,2010]must be used to construct D-Matrix, then add with the reconstructed image to increase the quality as shown in Figure 6.



Fig. 6 System Model of Decompression Stage of Algorithm (2).

c. Compress and Decompress Color Images

This algorithm is proposed for compressing the color medical images. First the RGB colors images are converted into $Y C_b C_r$ form, then applying algorithm (1) on each layer independently, this means each layer from $Y C_b C_r$ are compressed as a grayscale image. Figure 7 show that algorithm (1) is applied on each $Y C_b C_r$ layer.



Fig. 7 RGB Layers are Converted to YC_bC_r Layer, and then Compressed by Algorithm (1).

For decompression color images, apply decompression on each layer then collect all layers in one matrix $Y C_b C_r$ and convert $Y C_b C_r$ format to RGB color image.

Kufa Journal of Engineering (K.J.E) ISSN 2207-5528 Vol. 5, Issue 2, June, 2014 Printed in Iraq



5. Results and Discussion

The proposed algorithms are implemented on a number of medical images of different types as shown in **Figure 8**:



Fig. 8 Overview of Medical Test Images.

To see the benefits of the proposed quantization matrices on the quality of the compressed medical images in terms of PSNR and CR, **Table 1**, shows that (Q_a) is the best among different quantization matrices. Also **Table 1** illustrates that the proposed algorithm using framelet transform with the quantization matrix (Q_a) gives the best results.



Table 1 Comparison between Different Transformations in the Proposed Algorithm and
other Algorithms for Knee Image.

untization natrix	Proposed algorithm (1) using DWT		Prop algorit usi multiv	oosed thm (1) ing vavelet	Propo algorith using 1	sed m (1) FLT	Lossless compression based on polynomial
Qua	PSNR	CR	PSNR	CR	PSNR	CR	CR
Q_S	29.6906	5.2319	23.1187	8.9577	32.1433	<mark>5.2498</mark>	
Q_1	29.5503	<mark>6.6329</mark>	<mark>22.5687</mark>	11.4320	31.9922	6.6600	7.5298 (lossless
Q_2	30.5480	12.2919	29.3406	11.8203	32.1824	<mark>12.7078</mark>	without
Qa	30.5480	12.9038	<mark>29.3384</mark>	12.1960	32.1826	<mark>13.3636</mark>	quantization) [9]
Q_{B}	29.7807	0.0261	31.2533	5.9826	32.1587	10.2691	

Table 2 illustrates that the PSNR and CR for different images using FLT is better than DWT and DMWT.

Image	age Proposed algorithm (1) using DWT		Prop algori using mu	oosed ithm (1) ltiwavelet	Proposed algorithm (1) using FLT	
	PSNR	CR	PSNR CR		PSNR	CR
Brain1	25.6234	11.6309	29.9814	11.1484	30.1549	11.8582
Us	31.3289	11.3396	29.9814	11.1484	31.2616	12.0495
Artery	36.0551	9.0414	35.4165	8.4740	39.4400	8.8947
Xr1	29.8335	17.8883	29.4888	19.0155	30.7289	22.4809
Knee	30.5480	12.9038	29.3384	12.1960	32.1826	13.3636
Brain2	29.1421	14.5906	29.9734	13.4635	33.1217	14.2744

Table 2 Comparison between Different Algorithms for Medical Images.

Describing the comparison between the original image and the decompressed image using algorithm (1) is shown in **Figure 9**:





Fig. 9 Comparision between Original Image and Decompressed Image. (a) Original image Brain1.bmp (b) Decompressed Brain1,

Table 3 illustrates the results of testing the proposed algorithm (2) compared with algorithm (1) on different medical images.

Image	Algorithm (1)			Algorithm (2)		
PSNR CR Time		Time	PSNR	CR	Time	
Knee1.bmp (183 × 275)	29.9888	15.6453	19.8709 sec.	41.2525	5.2063	16.5356 sec.
Knee2.bmp (237 × 213)	31.6576	10.2349	32.1014 sec.	41.1764	3.0932	38.9937 sec.
MRI.bmp (230 × 220)	23.7493	11.6436	1 min, 27.5766 sec.	38.5547	4.0773	35.3546 sec.
X-ray1.bmp (194 × 259)	27.8120	12.3561	1 min, 1.3993 sec.	36.4956	4.0068	14.2674 sec.
X-ray2.bmp (210 × 240)	29.2432	13.2579	1 min, 17.9459 sec.	36.0333	5.1281	34.2931
US.bmp (203 × 249)	29.2243	13.1163	54.4308 sec.	34.9233	5.110	29.4118 sec

Table 3 The Proposed Algorithm (2) Compared with Algorithm (1).

Table 3 illustrates that the proposed algorithm (2) improves image quality compared with algorithm (1) with less time, but with low compression ratio. The algorithm (2) proposed for the mages which do not contain high psychovisual redundancy and have small dimensions, and small compression ratio, sufficient for it. As shown in **Figure 10**:





Fig. 10 Comparision between Original Image and Decompressed Image (a) Original US.bmp Size= 49.3623 Kbytes, (b) Decompressed US Compressed image Size = 9.6599 Kbytes

Finally testing the proposed algorithm (1) on a number of colour medical images of different types. The comparison between original and decompressed image is shown in **Figure11**.



Fig. 11 Comparison between Original Colour Medical Test Image and its Decompressed Image, (a) Original US (832×832) pixel Size 2028 Kbytes, (b) Decompressed US image Compressed image Size 127.304 Kbytes.

Good image quality and good compression ratio for the color medical images are illustrate in **Table 4** after applying algorithm (1).



Image	PSNR	CR
PET 1.jpg(256×192)	30.5626	12.3977
PET 2.bmp(241× 209)	31.6436	13.6875
SPECT.jpg(256×192)	33.1276	15.535
X-ray.bmp(168×300)	30.5174	7.4830
US.jpg (832×832)	30.7753	15.9303

Table 4 Color Images of the Proposed Algorithm (1).

Tables 5, 6 and 7 illustrate the effect of the quantization parameters (r, F and S) in equations (7 and 8) on the quality image and compression performance.

Image	r	PSNR	CR
	0.05	30.4145	6.5437
Brain1.bmp	0.1	30.3330	7.4881
380 × 380	0.25	30.0884	9.5827
	0.5	29.5141	11.1830
	0.05	31.7015	6.3114
US.bmp	0.1	31.6091	7.2687
205 imes 246	0.25	31.3193	8.9621
	0.5	30.6961	10.3709
	0.05	30.9606	10.6089
XR1	0.1	30.9340	11.6431
130 × 1 30	0.25	30.8313	15.3584
	0.5	30.5543	18.0147
Knee.bmp 512 × 512	0.05	32.8699	5.7028
	0.1	32.7430	7.0659
	0.25	32.1587	10.2691
	0.5	30.6560	13.2422

Table 5 Effect of r when F=5, s=2 and $r_D=0.45$.



Image	F	PSNR	CR
	2	30.2565	9.0607
Brain1.bmp	3	30.1789	9.2298
380 × 380	4	30.1559	9.4200
	5	30.0884	9.5827
	2	31.5142	8.2681
US.bmp	3	31.4322	8.4478
205×246	4	31.3882	8.6073
	5	31.3193	8.9621
	2	30.9032	13.5241
XR1	3	30.8868	13.9988
130 × 1 30	4	30.8341	15.1978
	5	30.8313	15.3584
Knee.bmp 512 × 512	2	32.5452	10.0472
	3	32.4422	10.0850
	4	32.3255	10.2279
	5	32.1587	10.2691

Table 6 Effect of F when r = 0.25, S = 2 and $r_D = 0.45$.

Tables 5 and 6 illustrates that the PSNR decreases when r and F increases, while CR increases.

Image	S	PSNR	CR
Davia 1 hour	2	30.0884	9.5827
380×380	3	30.3260	8.2344
000 / 000	4	30.3937	7.3387
US hmp	2	31.3193	8.9621
205×246	3	31.5916	7.6252
	4	31.6863	6.6972
VD1	2	30.8313	15.3584
130×130	3	30.9170	12.1945
130 / 130	4	31.0057	10.6289
Knee.bmp 512 × 512	2	32.1587	10.2691
	3	32.6554	8.3388
	4	32.8405	7.1668

Table 7 Effect of S when r = 0.25, F = 5 and $r_D = 0.45$.



 Table 7 illustrates that the increasing in parameter *s*, causes increasing in the image quality and decreasing in the CR.

6. Conclusion

Based on the experiments performed in this work, it can be concluded that:

- 1- To analyze image with size (N x N), the Framelet coefficient construct $(3N/2 \times 3N/2)$, where contains nine sub-bands, each component with size N/2. The properties of Framelet transform helped the algorithm to get good image quality, where the main reason for using Framelet transform is to reduce the image dimensions, while maintaining image quality. So, the high-frequencies coefficients are ignored. This is observed in the proposed algorithm (1).
- 2- In this work, other schemes have been tested, including dividing the image into blocks, then applying transformation on each block and compression all components using quantization matrix as shown in algorithm (2). This process gives a good quality and compressed the image as lossless compression.
- 3- Different types of quantization matrices have been studied and proposed in this work. The best results obtained with the proposed quantization matrices.
- 4- The effect of increasing the parameters (F, s and r), leads to increase the CR and decreasing the PSNR. These values are adjusted by the user to change the image quality and compression ratio.
- 5- The Minimize algorithm is used to reduce D-Matrix size. This process helps arithmetic coding to compress as much as possible.

7. References

- 1- Fatima B. Ibrahim, "Image Compression using Multilayer Feed Forward Artificial Neural Network and DCT", Journal of Applied Sciences Research, 6(10), pp. 1554-1560, 2010.
- 2- Adina Arthur and V.Saravanan, "Efficient Medical Image Compression Technique for Telemedicine Considering Online and Offline Application", Velammal Engineering College, Chennai, India, 2012.
- 3- Smitha J. Pinto and Jayanand P. Gawande, "Performance Analysis of Medical Image Compression Techniques", Cummins College of Engineering, Pune, India, IEEE, 2012.
- 4- Runhai Jiao and Biying Lin, "A Digital Image Watermarking Method Based on Tight Framelet", International Conference on Web Information Systems and Mining, China, IEEE, 2010.



- 5- RitamMisra .et al, "Denoising Neutral Current of a Power Transformer Measured During Impulse Test by Framelet Technique", IEEE 10th International Conference on the Properties and Applications of Dielectric Materials, Bangalore, India, IEEE, 2012.
- 6- David S. Taubman and Michael W. Marcellin, "JPEG2000 Image Compression Fundamentals", Kluwer Academiic Publishers, London, 2002.
- 7- Ban N. Thanoon and Loay E. George, "Image Compression using Hybrid Methods", Al-Nahrain University, Iraq, 2008.
- 8- Mohammed M. Siddeq, "JPEG and Sequential Search Algorithm Applied on Low-Frequency Sub- Band for Image Compression (JSS)", England, UK, Journal of Information and Computing Science, Vol. 5, No. 3, pp. 163-172, 2010.
- 9- Loay E.George and Ghadah Al-Khafaji, "Fast Lossless Compression of Medical Images based on Polynomial", International Journal of Computer Application (IJCA), 2013.