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Image Compression Techniques on-Board Small Satellites

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Abstract

Raw satellite images are considered high in resolution, especially multispectral images captured by remote sensing satellites. Hence, choosing the suitable compression technique for such images should be carefully considered, especially on-board small satellites, due to the limited resources. This paper presents an overview and classification of the major and state-of-the-art compression techniques utilized in most space missions launched during the last few decades, such as the Discrete Cosine Transform (DCT) and the Discrete Wavelet Transform (DWT)-based compression techniques. The pros and cons of the onboard compression methods are presented, giving their specifications and showing the differences among them to provide unified information about these methods for researchers and satellite imaging payload designers. Hence, some of these techniques are implemented, and comparisons are presented in the current work as examples to simulate an image compression system on board a small satellite using the MATLAB software package. This was achieved by employing three LANDSAT8, band6 satellite images. A wavelet selection was also considered for the DWT-based compression method, which gave the best results among the other methods through acquiring high values of compression ratio (CR) while maintaining the important scientific information of the image when reconstructed at the ground station.

Keywords: Remote sensing, Satellite Imaging, Image compression, Discrete Cosine Transform, Discrete Wavelet Transform.

تقنيات ضغط الصور على متن الأقمار الصناعية الصغيرة

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الخلاصه

الصور الفضائية الغير معالجة تعتبر عالية الدقة، وخاصة الصور متعددة الاطياف التي يتم التقاطها بواسطة أقمار التحسس النائي. لذا فينبغي الاهتمام والتمعن في اختيار التقنية المناسبة لضغط هذه الصورعلى متن الأقمار الصناعية الصغيرة تحديدا وذلك لمحدودية مواردها. هذا البحث يقدم ملخص وتصنيف لتقنيات ضغط الصور الرئيسية الحديثة التي تم استخدامها في معظم المهام للرحلات الفضائية التي تم اطلاقها في العقود القليلة الأخيرة، كالتقنيات التي تستند على دالة تحويل الجيب تمام المتجزئة أودالة تحويل المويجات المتجزئة. في هذا البحث تم تقديم الأيجابيات والسلبيات لطرق ضغط الصور على متن الأقمار الصناعية مع

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إعطاء مواصفاتها وإظهار الفروقات فيما بينها وذلك لتزويد الباحثين ومصممي الاحمال الخاصة بالتصوير الفضائي بمعلومات موحدة عن هذه الطرق. لذا، تم تنفيذ بعض هذه التقنيات في هذا العمل كأمثلة لمحاكاة منظومة لضغط الصور الفضائية على متن قمر صناعي صغير باستخدام برنامج ماتلاب، مع تقديم مقارنات للنتائج فيما بينها. تم تحقيق هذا من قبل الباحثة عن طريق توظيف الحزمة الطيفية السادسة لثلاث صور فضائية لقمر مراقبة الأرض لاندسات 8. كذلك تم في هذا العمل اختيار الموجة المناسبة لطريقة ضغط الصور الفضائية التي تستند الى دالة تحويل المويجات المتجزئة، هذه الطريقة التي أعطت افضل النتائج مقارنة بالطرق الأخرى من خلال الحصول على قيم اعلى من نسبة الضغط مع المحافظة على المعلومات العلمية المهمة للصورة الفضائية بعد إعادة تجميعها في المحطة الأرضية.

1. Introduction

1.1 Problem Statement

The masses of small satellites range from a few grams to 1000 kg. Hence, many factors should be considered when designing a small satellite, such as cost, memory, the computational resources onboard the satellite, and the bandwidth required to transmit data to the ground station. Therefore, image compression techniques are needed and should be carefully considered onboard small satellites according to the required mission. Hence, researchers and satellite designers have to choose the most suitable compression method among various methods used on-board small satellites to achieve a high compression ratio (CR); and, as a result, decrease the bandwidth required to transmit data from the satellite to earth while maintaining the essential scientific information of the image when reconstructed at the ground station.

1.2 Related works

1.2.1 Multispectral Images

Optical remote sensing uses sensors sensitive to multispectral bands, such as visible, near-infrared, and shortwave infrared bands, to form images of the earth's surface by detecting the solar radiation reflected from objects on the ground. Hence, multispectral images are used in remote sensing to a large degree, as presented in [1] and [2], and they are starting to be used in several terrestrial applications such as medical imagery and quality control, among others [3].

Various materials reflect and absorb radiation differently at different wavelengths. Thus, objects on the ground can be distinguished by their spectral reflectance signatures (bands) in remotely sensed images. The LANDSAT 8 satellite [4], as an example of Earth Observation (EO) satellites, captures 11 multispectral bands.

1.2.2 Image Compression

Image compression can be identified as decreasing the amount of data required to represent an image for storage or transmission purposes.

Image compression schemes are divided into two main categories: [5].

a. Lossless image compression: allows an image to be compressed and decompressed without any information loss, such as the CCSDS 123 algorithm [6].

b. Lossy image compression: a certain amount of data loss is accepted, such as JPEG [7] and JPEG2000 [8]. However, it provides a much higher compression ratio than lossless compression [9].

Satellite images usually have high resolution since they cover large areas of the earth’s surface [10]. Hence, image compression is needed to decrease the bandwidth required to transmit data from the satellite to the ground where the image is reconstructed while maintaining the reconstructed image quality as much as possible to preserve its scientific value.

1.2.3 Image Compression Techniques

The compression process can be achieved by removing the redundancy of an image. Hence, the compression techniques are classified according to the redundancy that these techniques remove.

Types of Redundancy

There are several types of redundancy in an image:

a. Spatial redundancy:

Spatial decorrelation methods, like prediction or transformation [11], are usually employed to remove spatial redundancy.

Prediction-based techniques: are used to predict the current pixel value from neighboring pixels, such as the Differential Pulse Code Modulation (DPCM) [12].

Transformation-based techniques: are used to transform an image from the spatial domain to either frequency or wavelet domains, mainly such as the Discrete Cosine Transform (DCT) [13] or the Discrete Wavelet Transform (DWT) [14].

b. Human vision redundancy:

Because human eyes are not quite sensitive to high frequency, removing human vision redundancy is usually achieved by *quantization*, with high-frequency elements being over-quantized or even deleted; hence quantization is used when dealing with lossy compression.

c. Statistical redundancy:

The lossless process that helps to remove this type of redundancy is called *entropy coding*, which explores the probability of symbols. The basic idea is to assign short codes to high-probability symbols and long codes to low-probability symbols, such as the popular Huffman or Arithmetic coding methods.

The block diagram in Figure 1 illustrates the image compression techniques, classified according to the type of redundancies they remove.

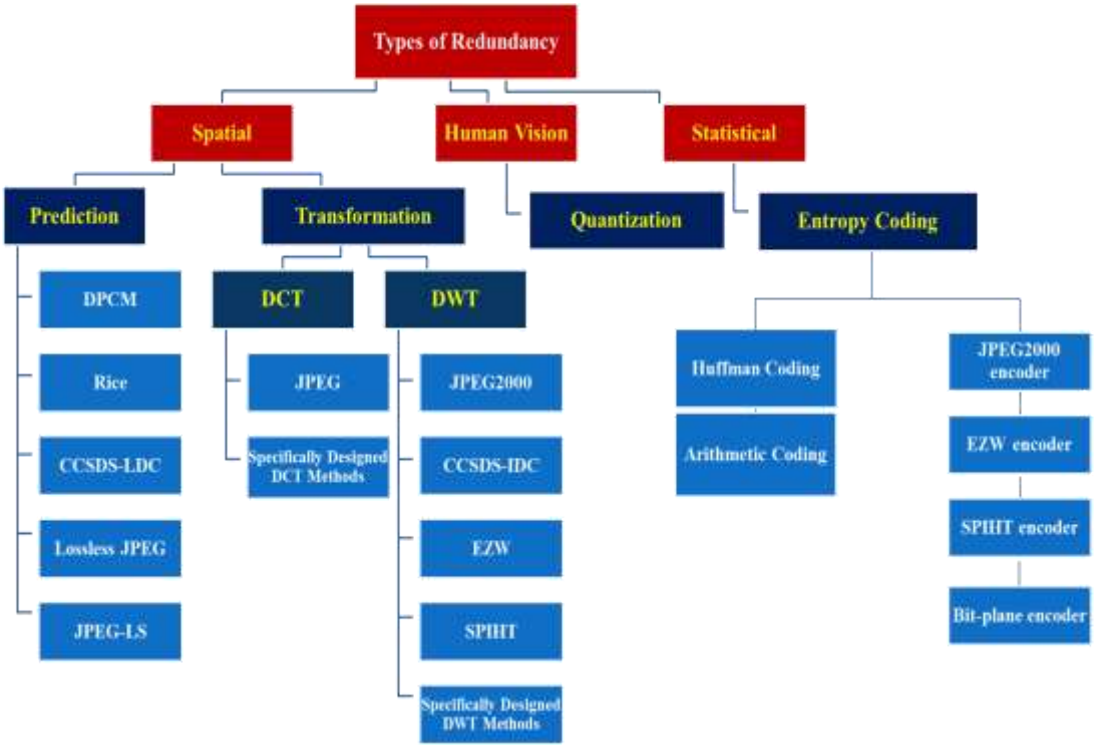


Figure 1: Classification of image compression techniques according to the type of redundancies they remove

The use of prediction methods can reduce the amount of information bits to represent the image due to the correlation property among adjacent pixels in the image. However, this type of image compression technique, such as DPCM, is not as competitive as transform coding techniques used in modern lossy image compression because predictive techniques have low compression ratios and worse reconstructed image quality than transform methods such as DCT and DWT. Although the newer versions of the prediction methods, such as Rice [15] and Lossless Data Compression (CCSDS-LDC) [16], are efficient. However, they produce lower compression ratios since they are considered lossless compression methods.

2. Methodology

Although it is impossible to reconstruct the exact original image using lossy image compression, it provides a much higher compression ratio than lossless compression. Hence, it will be used in the current work, which is dedicated to small satellites.

The procedure steps in the current work are:

1. The *image compression metrics* will be presented in section 2.1.
2. The *main steps* of the lossy compression algorithms used on-board satellites will be described in section 2.2.
3. The main *advantages and disadvantages* of each method will be presented in a comparison table accomplished by the author of this paper based on several related works. This table (Table 1) shows the best transform methods employed in satellite image compression applications.
4. The *algorithms of the best two methods,* based on the presented comparison, will be described in section 2.3 *towards being implemented,* and hence achieving objective and subjective results and comparisons in section 3, using MATLAB program, to simulate image compression systems onboard a small satellite, and the decompression process at the ground station.

2.1 Image Compression Metrics:

Choosing the suitable image compression method can be decided according to several parameters that are usually represented:

- *Objectively* (using the computed values of CR and PSNR, as defined below).
- *Subjectively* (evaluating the reconstructed image visually after it is decompressed).

Compression Ratio (*CR):* indicates the compression achieved for an image. It is a dimensionless value and can be computed as follows:

$$CR = \frac{Size\ of\ Original\ image\ (no.\ of\ bytes)}{Size\ of\ Compressed\ image\ (no.\ of\ bytes)}$$

Peak Signal to Noise Ratio (PSNR): gives a numerical value for the quality of an image after being compressed and decompressed. It can be computed as follows: (Its units are in (dB)).

$$PSNR = 10\ \log_{10}\frac{I^2}{MSE}$$

Where

I: The allowable image pixel intensity level

Example: for an 8bpp image, I= $(2^8 - 1)$ =255

Mean Square Error (MSE): Indicates the level of distortion by comparing the original data with the reconstructed data. It can be computed as follows:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(A_{i,j} - B_{i,j})^2$$

Where

A: Original image of size $M \times N$

B: Reconstructed image of size $M \times N$

2.2 The Main Steps of the Lossy Compression Algorithms used on-board Satellites

A typical architecture of a lossy image compression system usually starts with the transformation process, followed by quantization and finally entropy data coding, as shown in the block diagram in Figure 2.

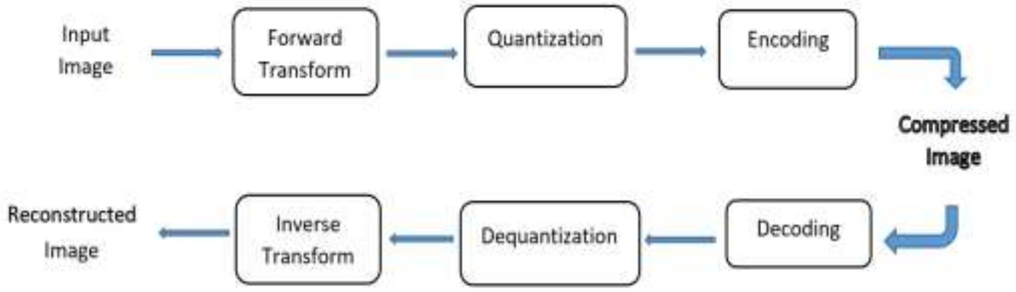


Figure 2: A Basic Transform-based Lossy Image Compression

Hence, the lossy compression steps can be presented as follows:

1. The first step is the *forward transform* (transformation from the spatial domain to the frequency domain), such as DCT and DWT, obtaining separated high and low-frequency coefficients to concentrate the most critical information signal into as few frequency components as possible.

Two-Dimensional transforms are usually used for image compression since 2-Dimensional matrices represent most types of images. There are several transform methods that can be used for image processing, such as: Karhunen-Loeve Transform (KLT) [17], [18], Discrete Fourier Transform (DFT) [19], [20], Walsh-Hadamard Transform (WHT) [21], Discrete Cosine Transform (DCT) [22] and Discrete Wavelet Transform (DWT) [11], [23], [24].

Each method has its advantages and disadvantages, as described in Table 1.

Table 1: Pros and Cons of the Transform Methods

Transform method	Advantages	Disadvantages
KLT [17]	• An optimal transformation technique always results in precisely uncorrelated transformed coefficients. • It has the most negligible mean square error value compared to other transformation techniques. • A high energy compaction property keeps as much energy as possible in a small number of coefficients.	A non-separable transform technique hence requires large computational resources compared to other transform techniques
DFT [19]	• Linear, separable and symmetric. • Presents an acceptable level of decorrelation and energy compaction characteristics.	• Yields lower values of decorrelation and energy compaction than DCT. • Mathematically Complex
WHT [21]	Less computations are required since only	• Very low energy

	addition and subtraction operations are needed.	compaction can be achieved compared to DCT. • Lower performance for higher compression ratios.
DCT [22]	• Requires a lower level of computational complexity compared to other methods. • It has a higher level of energy compaction compared to DFT and WHT. Hence, it is generally used for image compression.	• For higher levels of compression, it creates blocking artifacts in reconstructed images. • Compared to DWT, it achieves lower values of compression ratio.
DWT [11], [23]	• A multi-resolution transform technique. • Used for image compression to achieve higher values of compression ratio. • Maintains a good quality of a reconstructed image.	Most image compression techniques based on DWT usually require higher levels of computational complexity.

By comparing the transform methods presented in Table 1, it can be noticed that DCT and DWT transform outperformed the other methods, especially in energy compaction.
Hence, DCT and DWT~~T~~ represent the primary stage for the most commonly used lossy image compression techniques, and they have been utilized in most of the Earth Observation (EO) satellites with remote sensing multispectral imaging payloads launched during the last few decades.

2. The second step is *quantization*, which is represented by rounding the coefficients obtained after using a specific table or a threshold value decided by the user according to the transform method used to achieve a specific compression ratio. Hence, this step is not used with lossless image compression systems as it is considered (irreversible), since despite using the de-quantization process in lossy image compression systems to reverse the steps, the information loss resulting from the rounding process cannot be retrieved.

3. The third forward step is *entropy encoding*, in which the coding of the quantized data occurs, optimizing the representation of the information to achieve a further reduction in the bit rate to increase the compression in a lossless process, which can be optional in some coding systems [11]. There are several encoding methods for compression depending on the transform technique employed.

The entropy coding for DCT-based compression systems, for example, the Joint Photographic Experts Group (JPEG) algorithm, is often represented by Huffman [25] or Arithmetic coding systems [25] that exploit the probability of the symbols, giving a short code to the high probability symbol and a long code to the low probability symbol.

The entropy coding for the DWT-based compression methods, on the other hand, can be represented by several methods such as JPEG2000, Embedded Zero Tree Wavelet algorithm (EZW) [26], Set Partitioning in Hierarchical Trees (SPIHT) [27], and the Image Data Compression (CCSDS-IDC) [9]. The coding for all these DWT-based methods depends on separating the significant values (compared to a specific threshold) from the insignificant ones.
Performing the above three steps in reverse will lead to the decompression and reconstruction of the image.

2.3 Main Compression Algorithms to be implemented and compared in this work

As was presented earlier in this paper, despite their drawbacks, the DCT and the DWT transform methods represent the primary stage for the most commonly used lossy image compression techniques, and they have been utilized in most of the Earth Observation (EO) satellites with remote sensing multispectral imaging payloads launched during the last few decades.

2.3.1 Discrete Cosine Transform (DCT)

Since it was first used for image compression in 1974, DCT has proved to have specific properties that made it suitable for image compression. Some of these properties are:

a. High energy compaction: concentrating the essential information signal into as few low-frequency components as possible.

b. It does not require large amounts of computational resources.

Hence, compression techniques based on DCT were previously widely implemented onboard older satellites. This technique, however, has several drawbacks, such as:

a. The blocking artifacts appear at higher values of compression ratio.

b. Limited values of compression ratio are achieved.

When the 2D-DCT is used as the forward transform step, the quantization step can be achieved by dividing the resulting coefficients by the JPEG standard monochrome quantization table (Quality Q-table) and rounding the results after this division. A scaling factor (Q-Factor) may be used to increase the compression ratio.

When the DCT-based image compression JPEG standard is used, the image will be divided into blocks of 8×8 pixels to decrease the arithmetic operations and accomplish the process faster.

Hence, when the 2D-DCT algorithm is applied to an 8×8 pixels block, it can be calculated by equation (1) [7] [22]:

$$S(u,v) = \frac{1}{4} C(u)C(v) \sum_{x=0}^{7} \sum_{y=0}^{7} s(x,y) \cos[(2x+1)u\pi/16] \cos[(2y+1)v\pi/16] \quad (1)$$

Where

u: number of horizontal DCT coefficients $0 \leq u < 8$

v: number of vertical DCT coefficients $0 \leq v < 8$

$C(u) = 1/\sqrt{2} \quad if\ u = 0$

$C(u) = 1 \quad if\ u > 0$

$C(v) = 1/\sqrt{2} \quad if\ v = 0$

$C(v) = 1 \quad if\ v > 0$

$s(x,y) =$ the pixel value at coordinates (x,y)

$S(u,v) =$ the DCT coefficient at coordinates (u,v)

The quantization process can be achieved using equation (2):

$$D(u,v) = round\left(\frac{S(u,v)}{Q(u,v)}\right) \quad (2)$$

Where $Q(u,v)$: represents the Q-table element at coordinates (u,v)

$D(u,v)$: represents the quantized element at coordinates (u,v)

While the inverse of 2D-DCT (2D-IDCT) can be calculated using equation (3):

$$s(x,y) = \frac{1}{4} \sum_{u=0}^{7} \sum_{v=0}^{7} C(u)C(v)S(u,v) \cos[(2x+1)u\pi/16] \cos[(2y+1)v\pi/16] \quad (3)$$

Where

For the reconstructed image:
x: the pixel row, for the integers $0 \leq x < 8$
y: the pixel column, for the integers $0 \leq y < 8$
$s(x, y)$: is the reconstructed pixel value at coordinates (x, y)

2.3.2 Discrete Wavelet Transform (DWT)

DWT-based compression techniques have recently been used more than the DCT [28] since:

a. It is a multi-resolution transform; variable compression can be easily achieved.
b. No clear appearance of blocking artifacts occurs since the 2D-DWT transform functions a whole image or large partitions of the image.
c. Higher compression ratios can be achieved using this method.

Hence, it is noticed that DWT-based compression techniques are used on the payloads of more recently launched satellites. However, to achieve a higher level of compression using this method, a higher number of DWT decomposition stages is needed, which leads to:

a. An increase in computational complexity.
b. A degradation of reconstruction quality.
c. Higher power consumption.

The basic idea of DWT compression is to convert the image data into wavelets, using specific low and high pass filters.

The thresholding and quantization steps will be used when the 2D-DWT is used as the forward transform step. The thresholding process includes setting all 2D-DWT coefficients that are less than a particular value (threshold) to zero to remove part of the information from the DWT coefficients and increase the compression. The higher the threshold value, the higher CR can be obtained, but at the expense of the quality. The threshold value can be calculated using several equations according to the thresholding method employed. The quantization is an irreversible process represented by rounding the resulting coefficients after the thresholding process.

Each level of the 2D- DWT transform creates two types of coefficients:

- The approximation coefficients (cA) (represent the image's low frequency, the most crucial information that can be recognized by human eyes much better than high-frequency information).
- The detail coefficients are identified by the horizontal (cH), vertical (cV), and diagonal (cD) coefficients (representing the high frequency, less critical information of the image).

Figure 3 shows two levels of 2D-DWT transform for a satellite image (Erbil).

Original Satellite Image 1 level 2D-DWT 2 levels 2D-DWT

Figure 3: 2D-DWT satellite image compression (2-levels)

A whole image, or large partitions of the image, can be used with the 2D-DWT transform to avoid the artifact problem caused by image blocking as in 2D-DCT.
The 2D-DWT of image $f(x,y)$ of size $M\times N$ can be obtained using equations (4), (5), (6), and (7) [29]:

1. Approximation coefficients

$$W_{\varphi}(j_0, m, n) = \frac{1}{\sqrt{M.N}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\varphi_{j0,m,n}(x,y) \quad (4)$$

Where $\varphi_{j,m,n}(x,y) = 2^{j/2}\,\varphi(2^j x - m, 2^j y - n)$ (5)

2. Detail coefficients

$$W_{\psi}^{i}(j, m, n) = \frac{1}{\sqrt{M.N}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\psi_{j,m,n}^{i}(x,y), \quad i=\{H, V, D\} \quad (6)$$

Where $\psi_{j,m,n}^{i}(x,y) = 2^{j/2}\,\psi^{i}(2^j x - m, 2^j y - n)$ (7)

Where j_0: An arbitrary starting scale
m, n: 2D-DWT Coefficients coordinates
$W_{\varphi}(j_0, m, n)$: Approximation coefficients of $f(x,y)$ at scale j_0
$W_{\psi}^{i}(j, m, n)$: Detail coefficients (horizontal (H), vertical (V), or diagonal (D)) for scales $j \geq j_0$
x, y: Pixels coordinates
$f(x,y)$: the pixel value at coordinates (x,y)
Usually: $j_{0=0}$, N=M= 2^J
Hence, j= 0, 1, 2, …, *J-1*
m = n = 0, 1, 2, …, 2^j -1

The 2D-IDWT (the reconstructed image) can be obtained using equation (8) [29]:

$$f(x,y) = \frac{1}{\sqrt{M.N}}\sum_m\sum_n W_{\varphi}(j0,m,n)\varphi_{j0,m,n}(x,y) + \frac{1}{\sqrt{M.N}}\sum_{i=H,V,D}\sum_{j=j0}^{\infty}\sum_m\sum_n W_{\psi}^{i}(j,m,n)\,\psi_{j,m,n}^{i}(x,y) \quad (8)$$

- Hence, the established DCT and DWT-based Transform compression methods were implemented in this work as the best examples of transform-based compression methods employed on-board satellites. Even though the DCT is being employed to a lesser degree onboard satellites than DWT lately due to blocking artifacts, it can be employed as part of a hybrid method to improve the compression, as presented in [30]. A comparison was made after that to evaluate each method's properties and which is more feasible to be employed onboard small satellites.

Future works can present other compression methods since each method should be presented in detail.

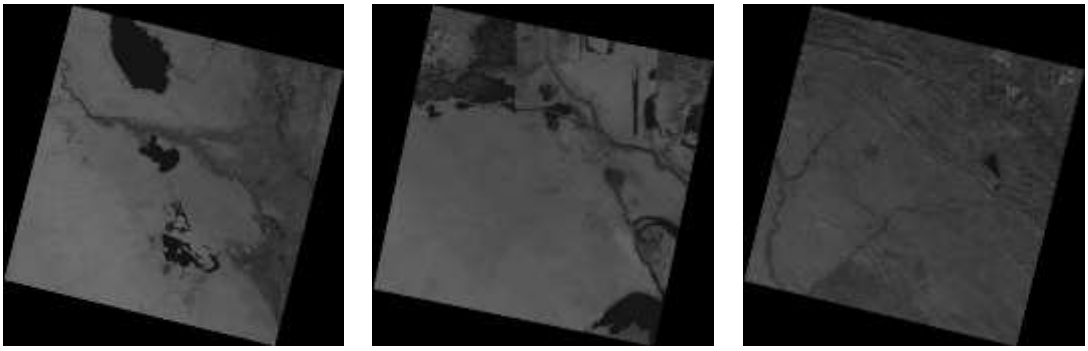
- Each method was implemented in the current work using MATLAB software, simulating an image compression system onboard a small satellite and a satellite image reconstruction at the ground station.

However, encoding and decoding steps were not considered in this work for both compression methods. Due to:

➢ As presented earlier in this section, the variations of the entropy coding techniques used for image compression lead to difficulty covering all these techniques in one paper.
➢ The compression ratio (CR) results can be affected according to the encoder type to achieve a feasible comparison among the transform methods used.
➢ They can be optional in some coding systems [11].

However, these techniques can be presented in detail in future works.

- Three high-resolution satellite images in the current work as shown in Figure 4. The researcher downloaded them from the United States Geological Survey (USGS) website [31]. The specifications for these images are described in Table 2:



Baghdad **Basra** **Erbil**

Figure 4: LANDSAT8 Band6 Satellite Images used in the Current Work

Table 2: The specifications of the satellite images used in the current work

Image	Type	Size (MB)	Resolution (pixels)	Bit depth (bpp)
Baghdad	TIF	82.5	7924×7924	16
Basra	TIF	86.6	7924×7924	16
Erbil	TIF	82.8	7924×7924	16

- These images were captured by the LANDSAT8 remote sensing satellite. The LANDSAT8 images were chosen to be used in the current work due to:

1. LANDSAT8, the latest version of the LANDSAT satellites, provides high-quality visible and infrared images of all landmass and near-coastal areas on the Earth [4].
2. Continually refreshing an existing Landsat database [4].
3. The fact that they can be acquired by subscribing to the USGS (United States Geological Survey) website [31] without any charges.

- LANDSAT8 captures 11 multispectral bands to form the data set of an image. However, only Band 6 (B6) images (Short Wave Infrared (SWIR-1)), which fall in the non-visible area of the spectrum, were used in this work for two reasons:

1. Band 6 has more visual clarity than the other bands, as shown below in Figure 5, which illustrates the 11 Multispectral bands of the Baghdad satellite image captured by LANDSAT8. This clarity eases the process of subjective comparison between images before and after compression.

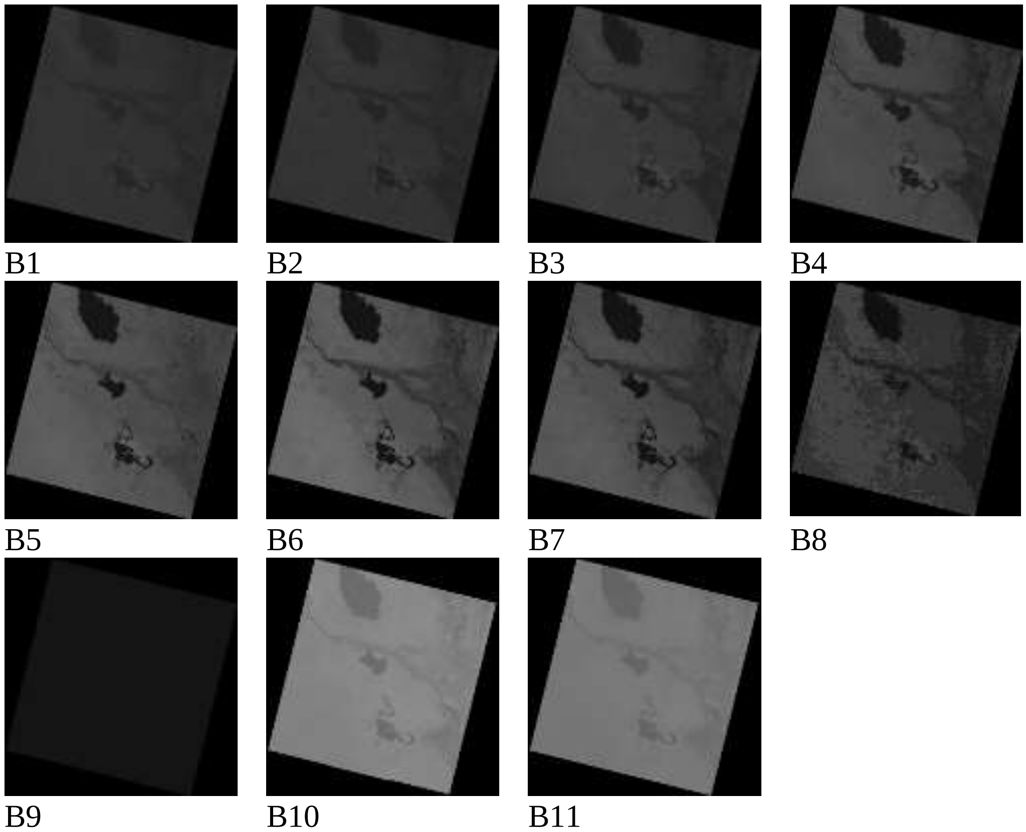


Figure 5: The 11 Multispectral bands of Baghdad satellite image captured by LANDSAT8

2. This band discriminates the moisture content of soil and vegetation and penetrates thin clouds [32]. Hence, B6 satellite images are needed to help evaluate several critical environmental problems currently widespread in (Iraq), especially desertification. Hence, the main objective of a proposed Earth resources mission would be to provide meaningful scientific data to the Iraqi environmental scientists in order for them to quantify the environmental problems in Iraq better.

3. Results and discussion

Objective and subjective *results* and *comparisons* were made for:

1. The DCT-based compression method.
2. The DWT-based compression method.

Entropy encoding and decoding steps will not be considered in this work for the reasons mentioned in section 2.

3.1 2D-DCT and 2D-DWT Results

Two-Dimensional transforms are usually used for image compression since 2-Dimensional matrices represent most types of images.

3.1.1 2D-DCT-based Compression Results

The objective results for the 2D-DCT transform were represented by the CR and the PSNR, which were computed as presented in section 2.1 using the MATLAB software package. The chart in Figure 6 illustrates these results for the Baghdad satellite image.

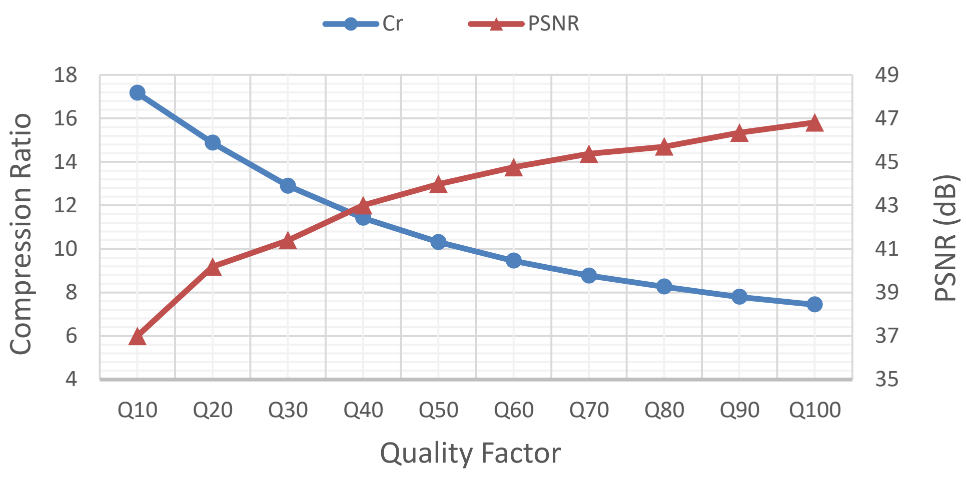


Figure 6: 2D-DCT objective results (represented by CR and PSNR)

It is evident from the results in Figure 6 that the PSNR is proportional to the quality factor (Q). The CR, on the other hand, is inversely proportional to that factor. The quality factor, presented in section 2.3.1, is usually employed to change the Quality matrix values by scaling it up or down (since Q is considered inversely proportional to it) to control the quantization and rounding processes (equation 2) and, as a result, control the CR and PSNR values as required. Hence, the less the value of the quality factor used, the more degradation of the reconstructed image was visualized (due to the increase of the values of the quality matrix elements) and vice versa. As a result, the relation between the CR and PSNR is inversely proportional.

3.1.2 2D-DWT-based Compression Results

Before any objective or subjective computations, wavelet selection should be considered when using the DWT compression. Hence, six different types of orthogonal and biorthogonal wavelets were examined in this work for two levels of 2D-DWT satellite image compression and decompression (by comparing the PSNR values of the reconstructed satellite images Baghdad, Basra, and Erbil) to choose the most appropriate wavelet to be employed for this method, as can be seen in Figure 7.

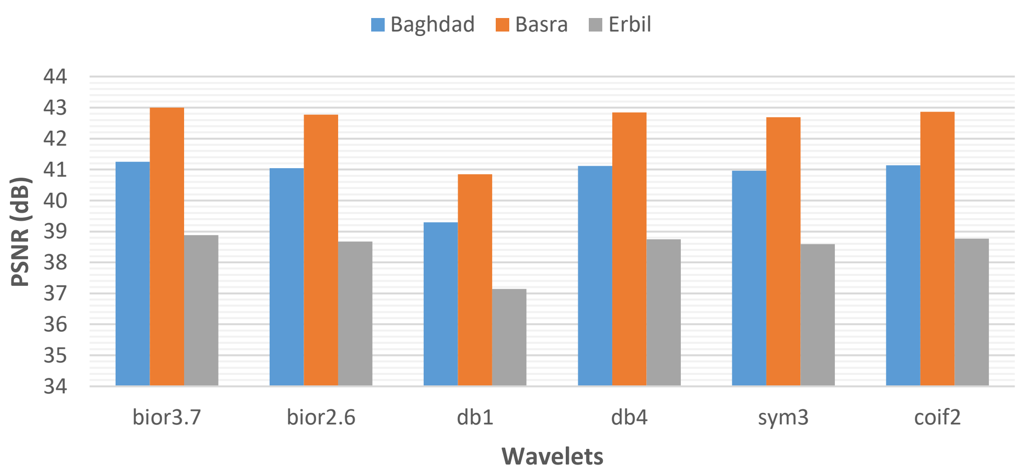


Figure 7: Wavelet Selection

It can be noticed from the wavelet selection process results that even though the differences in PSNR values are not significant among the six wavelets used (except for db1, since it represents the simplest form of wavelets), the biorthogonal wavelet (known as "bior 3.7") gave the highest PSNR value among the other wavelets. Hence, it will be employed in this method for all three satellite images used in the current work.

The objective results obtained from implementing this method (represented by CR and PSNR) were computed using the MATLAB software package, as given in section 2.1 of this paper. These parameters can be controlled by changing the threshold value mentioned earlier in section 2.3.2 of the current work. The chart in Figure 8 illustrates these results for the Baghdad satellite image.

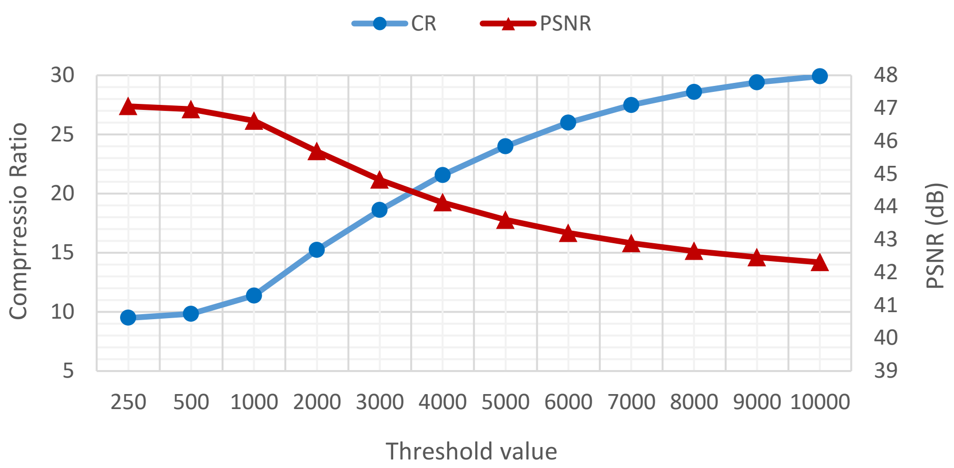


Figure 8: Second level 2D-DWT objective results (Baghdad Image)

It can be noticed from Figure 8 that the higher the threshold value, the higher CR can be obtained, but at the expense of the quality (PSNR).

3.2 Objective comparisons

The objective results (CR and PSNR) were calculated based on the change in quality factor *(Q)* for the DCT compression algorithm, while the change in the threshold value was used in the DWT-based compression method. Hence, the final objective criterion for this comparison was the values of PSNR according to different compression ratio (CR) values obtained for each method to unify the baseline and ensure feasible comparisons; this is shown in the graphs (Figures 9, 10, and 11) for the three satellite images used in the current work.

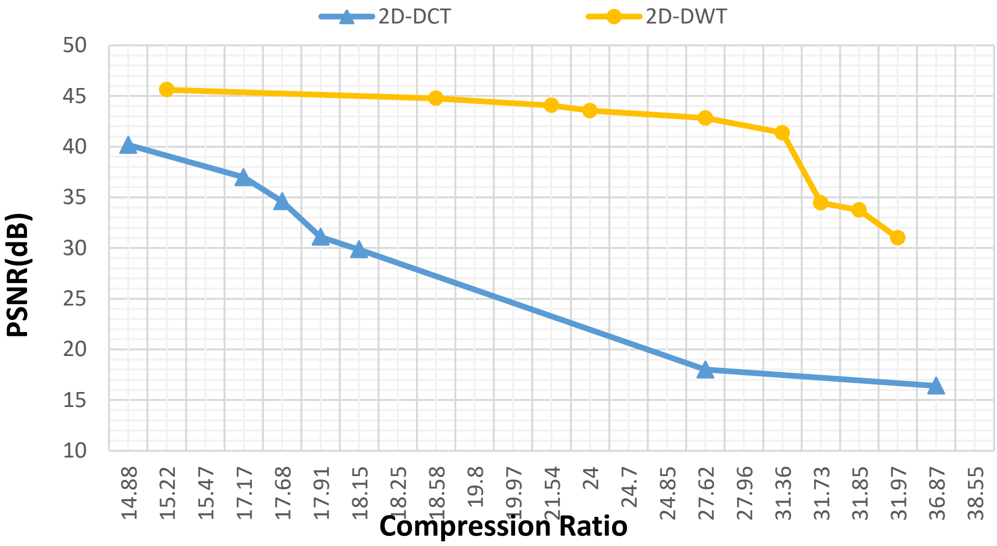


Figure 9: Objective comparison between DCT and DWT (Baghdad sat. image)

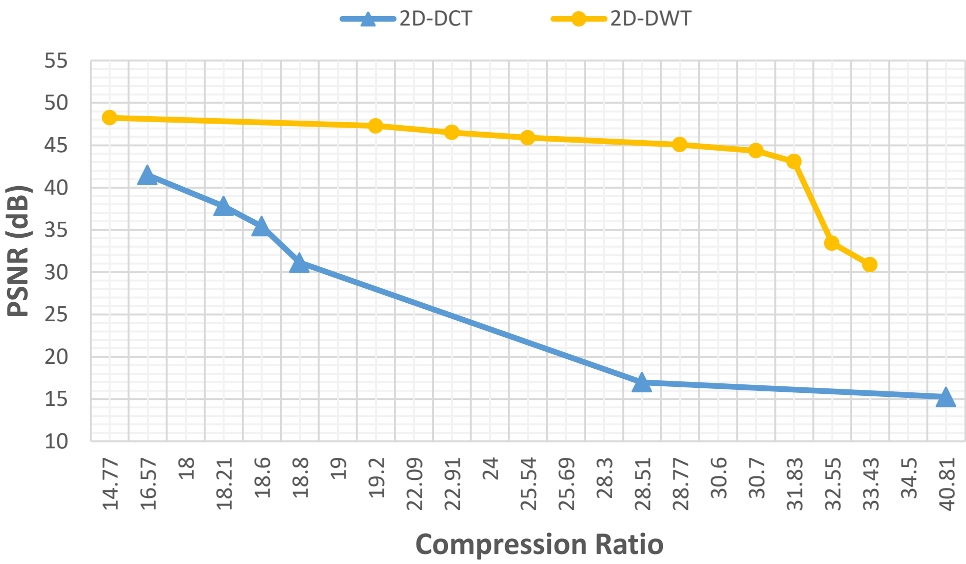


Figure 10: Objective comparison between DCT and DWT (Basra sat. image)

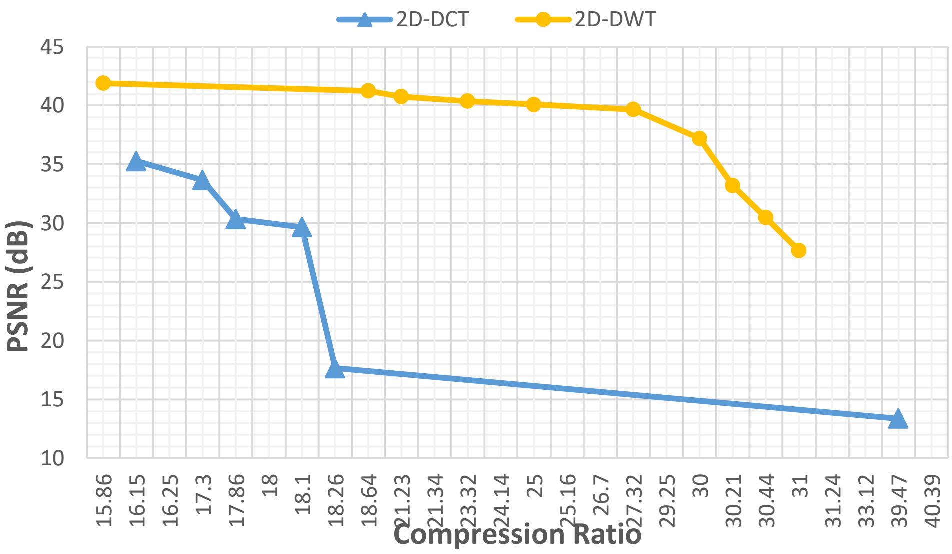
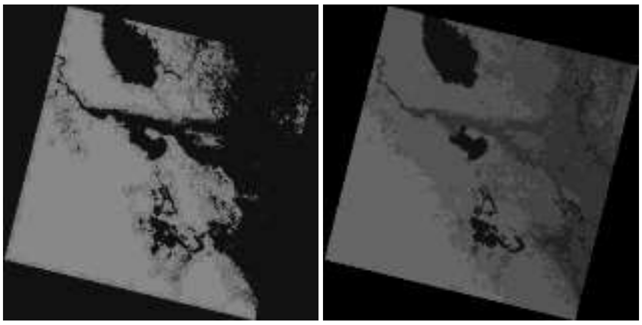


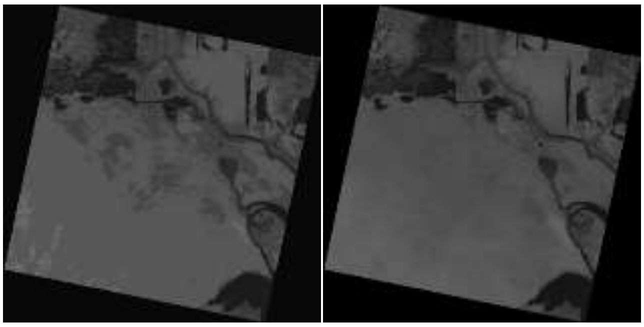
Figure 11: Objective comparison between DCT and DWT (Erbil sat. image)

3.2 Subjective comparisons

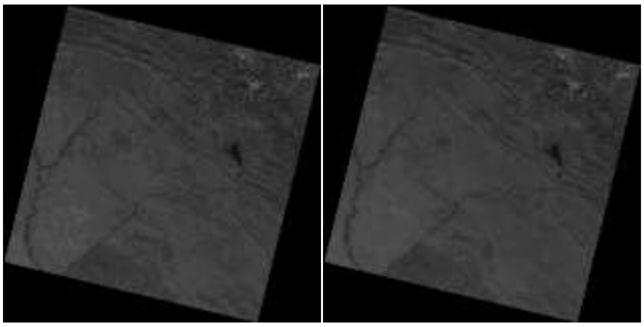
The subjective comparisons of the reconstructed satellite images using the two methods can be observed visually in Figure 12 by using Baghdad, Basra, and Erbil satellite images seen before in Figure 4.



a (DCT) **a** (DWT)



b (DCT) **b** (DWT)



c (DCT) **c** (DWT)

Figure 12: Visual comparison between DCT and DWT methods (Decompressed Image) **a** Baghdad satellite image (CR value around 28), **b** Basra satellite image (CR value around 18.6), **c** Erbil satellite image (CR value around 16.5)

3.3 Discussion of the Results

It can be deduced from the objective and subjective comparisons that:

a. The DWT method outperforms the DCT method in terms of the PSNR values in the objective results and hence, the reconstructed image quality (no blocking artifacts are noticed) in the subjective results.

b. With higher compression ratio values, the DCT-based compression method gives fewer PSNR values (less quality of the reconstructed images) due to the increased blocking artifacts. Hence, it was noticed through the visual comparison that the Baghdad DCT image was the worst among the other DCT images due to the high compression ratio value (28) chosen to compare with the DWT method. At the same time, better quality for the DCT reconstructed Basra image when CR was (18.6), and the best image quality was for the DCT reconstructed Erbil image employing (16.5) as a CR value for comparison.

4. Conclusion

This paper reviewed and classified the image compression systems utilized onboard small satellites during the last few decades. After describing and comparing the advantages and disadvantages of each transform method, it was concluded that the DCT and DWT transform techniques are the best to be employed for satellite image compression.

Three LANDSAT8, band 6 satellite images were employed to implement the DCT and DWT- based compression methods, simulating an image compression system on-board a small satellite and the decompression process at the ground station.

It was concluded that the DWT-transform, using the (bior 3.7) wavelet, outperformed the other methods in terms of the objective results represented by the CR and PSNR values and the subjective results represented by the visual comparisons among the reconstructed satellite images. This was achieved through acquiring high values of compression ratio (CR) while maintaining the essential scientific information of the image when reconstructed at the ground station.

Hence, the DWT can be considered the most appropriate transform-based compression technique to be employed on-board small satellites, whereas the other transform methods can be employed only in some hybrid methods to improve the compression or replace the entropy encoder.

However, several compression methods based on DWT are identified according to the entropy encoder to be used and can be presented in detail and implemented in future works.

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