Compression Ratio and Peak Signal to Noise Ratio in Grayscale Image Compression using Wavelet

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Abstract
Computer technology to human needs that touch every aspect of life, ranging from household appliances to robots for the expedition in space. The development of Internet and multimedia technologies that grow exponentially, resulting in the amount of information managed by computer is necessary. This causes serious problems in storage and transmission image data. Therefore, should be considered a way to compress data so that the storage capacity required will be smaller.
In this research wanted to know the influence of wavelet to the compression ratio and to the PSNR (Peak Signal to Noise Ratio). Then the compression ratio and PSNR results than would be obtained so that the optimal wavelet, which has a high compression ratio and PSNR. Wavelet is used Daubechies, Coiflet, and Symlet families. Test images used are 8-bit grayscale images of size 512x512.
Wavelet which has the highest compression ratio in each family is Haar, Coiflet 1, and Symlet 2. While the wavelet which has the highest PSNR in each family is Haar, Coiflet 3, and Symlet 5. For wavelet which has a compression ratio and PSNR values are optimal for each family are Haar, Coiflet 3, and Symlet 5.

Keywords
Compression ratio, PSNR, image, compression, wavelet

I. Introduction

Computer technology to human needs that touch every aspect of life, ranging from household appliances to robots for the expedition in space. The development of the Internet and multimedia technologies grows exponentially, this results in the amount of information to be managed by computers [1]. In addition, the use of digital images is growing rapidly. This causes serious problems in image data storage and transmission. Therefore, management needs to consider the volume of image data storage capacity and transmission bandwidth [2]. Gibson, et.al [3] warns that digital signal requires more bits per second (bps) in both the storage and delivery, so it results in higher costs.

The concept of graphs and images appear to represent pages of numerical data that need a lot of time to waste. A graph or image is a translation of data in the form of images that can represent the data. Image data is a combination of information and redundancy, the information is maintained by the data because it contains the meaning and designation data. While the redundancies are part of data that can be reduced, compressed, or eliminated.

Therefore, it is important to consider a way to compress data in order to minimize the storage capacity required. If, at any time, the data are needed the user can just return it to the original size. Although, today the price of storage is also getting cheaper and bigger in size but it will still be more effective if the data size can be reduced so that it can save more space for other data needed. Besides, in the field of multimedia communications network, if the data is not compressed a large bandwidth and a long time are needed to process the transmission of the data [4]. The solution of this problem is to compress data to reduce storage space and transmission time [1]. This proves the importance of data compression on large data to be transmitted. For example a video will save more bandwidth use when the data is already compressed.

At present many methods are available for data compression, one of which is the use of wavelet. This study tries to find out the influence of wavelet towards the compression ratio and to the PSNR (Peak Signal to Noise Ratio). Then the compression ratio and PSNR results are compared to find the optimum wavelet, which has a high compression ratio and PSNR. Wavelet used are Daubechies family of Haar (Daubechies 1), Daubechies 2, Daubechies 3, Daubechies 4, Daubechies 5), and Coiflet families, and Symlet families. Test images used are 8-bit grayscale images of 512x512 size.

II. Literature Reviews

A. Image compression

Currently, many applications want a representation of the image with minimal storage [5]. In general, the representation of digital image requires a large memory. The greater the size of a particular image, the greater the memory it needs. On the other hand, most images contain duplicate data. There are two duplicated parts of data in the image. The first is the existence of a pixel that has the same intensity as its neighboring pixels. These duplicated pixels waste more storage space. The second is that the image contains many repeated sections (regions). These identical sections do not need to be encoded many times to avoid redundancies and, therefore, we need an image compression to minimize the memory requirement in representing a digital image. The general principle used in the process of image compression is to reduce duplication of data within the image so that the memory needed to represent the image is smaller than the original image [5].

B. Wavelet

Wavelet is a mathematical function that divides the data into different frequency components, then fits each component with a resolution suitable for its scale [6]. Wavelet is a waveform that effectively has a duration limit of zero mean value. Some applications that have been successfully realized by utilizing such wavelet are image data compression, watermarking, edge detection, radar systems, and encoding fingerprints. Stollnitz et.al [7] says that one of the nature of wavelet is its infrequency. In fact, there are many coefficients in the representation of wavelet with very small

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or zero value. This characteristic gives the opportunity to perform image data compression. The application of wavelet transform in digital image processing uses the Discrete Wavelet Transform or DWT. Wavelet is a base, the wavelet base is derived from a scaling function which properties are assembled from a number of self copies that has been dilated, translated and scaled. This function is derived from the dilation equation, which is considered as the basis of wavelet theory. From the scaling equation of this function a wavelet equations of the first (known as mother wavelet) can be formed as follows:

$$\psi_{ab}(x) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{x-b}{a}\right) \tag{1}$$

$\psi a,b(\cdot)$ is obtained by scaling the wavelet at time b and scale a, where $\psi(x)$ represents the wavelet.

The main properties of wavelet transform in still image compression is the occurrence of minimum distortion in the reconstructed image even when exercising removal transform coefficients are near zero. Wavelet transforms on an image results in many subfields images with very small magnitude. In determining non-negative threshold, the elements of image with very small subfields can zeroed so as to produce a very rare matrix. The existence of the very rare matrix will make it easier to be transmitted and stored, even the result of image reconstruction with threshold (quantization) can provide visual results for bare eyes. In the wavelet transform process for 2-dimensional image, there are two ways to decompose the pixel values, the standard decomposition and nonstandard decomposition [7]. Each method is obtained based on wavelet transform 1-dimensional. When the standard decomposition processes an image, the first is by using a wavelet transform 1-dimensional image on each row. This process will generate a mean value along with detail coefficients for each row. The second is by using wavelet transform 1-dimensional image on each column. The process results in the form of detail coefficients and one coefficient average. Nonstandard Decomposition transformation is obtained by combining pairs of rows and columns alternately transformation. In the first step wavelet transform 1-dimensional line is applied, then followed by a wavelet transform 1-dimensional column. In the decomposition level 1, the image will be divided into 4 sub bands, they are HH, HL, LH, and LL sub bands. HH sub band image gives details on the diagonal, HL sub band provides detailed images in the horizontal direction, the LH sub band provides detailed images in the vertical direction. While the LL sub band is a low-resolution residue that has low frequency components, which are often referred to as the average image. LL sub band is divided again at the time of decomposition at a higher level. The process is repeated according to the desired level.

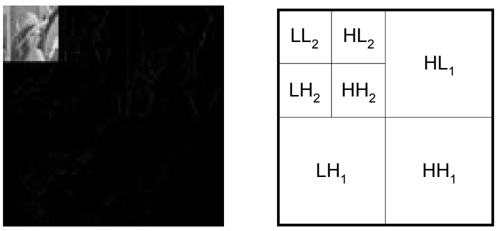

Fig. 1: Image Decomposition

Currently, wavelet applications receive much attention in the research world, one of which functions to analyze an image. As a technique of 2-dimensional discrete signal analysis, for example in analyzing images, wavelet decomposes signal into signal average, details of vertical, horizontal and diagonal at some desired level. In addition, wavelet decomposes the original signal into signals in some frequency bands (called multi-resolution analysis.) The analysis can be done by applying the Discrete Wavelet Transform [8] or standard decomposition techniques and non-standard Haar with wavelet [9,10]. The feature (signature) image generated by wavelet is taken from a wavelet coefficient at a certain level (3, 4 or 5) and can be transformed to a much smaller than the original image.

C. Compression ratio and PSNR

Benchmarks in image data compression are the compression ratio and PSNR (Peak Signal to Noise Ratio). The compression ratio is used to measure the ability of data compression by comparing the size of the image being compressed to the size of the original image. The greater the compression ratio means the better the wavelet function. PSNR is one of the parameters that can be used to quantify image quality. PSNR parameter is often used as a benchmark level of similarity between reconstructed image and the original image. Larger PSNR will produce better image quality.

III. Research Methodology

A. Materials Research

The wavelet used in this research is Daubechies family of Haar (Daubechies 1), Daubechies 2, Daubechies 3, Daubechies 4, Daubechies 5, and Coiflet families, and Symlet family. The test images used are 8-bit grayscale images, namely Bridge.bmp, City.bmp, and Clown.bmp with size 512 x 512. The test images can be seen in Fig. 2.

(a) (b)

(c)

Fig. 2: Test Image

(a). Bridge, (b). City, (c). Clown

B. Research Steps

Research steps are as follow. The first is to test several wavelet for compression ratio, and wavelet to the PSNR for several test images. The diagram of the trial process image compression and image decompression can be seen in Fig. 3. It consists of two process, compression process and decompression process.

The compression process consists discrete wavelet transform (DWT), quantization. The decompression process has the inverse operations of compression process.

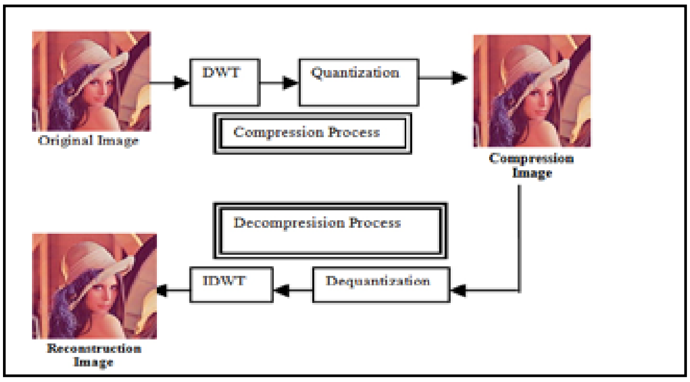

Fig. 3: Compression and Decompression Process

The results of these tests can, then, be analyzed the influence of wavelet to the compression ratio, and on the PSNR. Later, it can also analyze the effects of compression ratio and PSNR of the wavelet in order to find an optimum wavelet in every family.

IV. Results and Discussion

A. Wavelet versus Compression Ratio

One success measurement in image data compression is the compression ratio. The compression ratio is to measure the ability of data compression by comparing the sizes of the image being compressed with the original size. The greater the compression ratio means the better the wave function-in short. The test results of the wavelet influence towards the compression ratio of several test images can be seen in table 1.

Table 1: Compression Ratio Results (in %) for wavelet and Test Image

Wavelet\Image	Bridge	City	Clown
Haar	99.312	99.313	99.312
Daubechies 2	99.237	99.237	99.237
Daubechies 3	99.156	99.156	99.156
Daubechies 4	99.075	99.075	99.075
Daubechies 5	98.987	98.987	98.987
Coiflet 1	99.156	99.156	99.156
Coiflet 2	98.902	98.902	98.902
Coiflet 3	98.682	98.682	98.682
Coiflet 4	98.401	98.401	98.401
Coiflet 5	98.103	98.103	98.103
Symlet 2	99.237	99.237	99.237
Symlet 3	99.156	99.156	99.156
Symlet 4	99.075	99.075	99.075
Symlet 5	98.987	98.987	98.992
Symlet 6	98.902	98.902	98.902
Symlet 7	98.812	98.812	98.812
Symlet 8	98.723	98.723	98.723

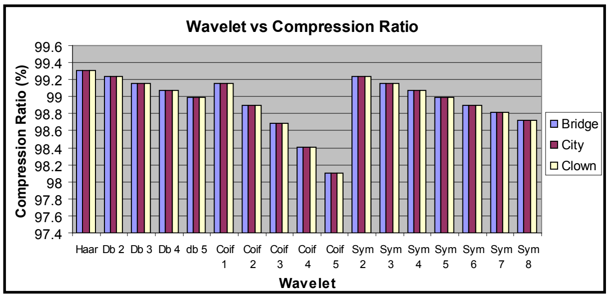

Fig. 4: Wavelet versus Compression Ratio

Based on table 1 and Fig. 4, it shows that Haar has the highest compression ratio, while for the Daubechies family, Coiflet 1 for family Coiflet, and wavelet Symlet 2 for Symlet family.

B. Wavelet versus PSNR

PSNR is one success measurement in image data compression. PSNR is used to quantify the image quality. The larger PSNR value means the better its wavelet function is, it means the reconstructed image is so much closer to the original image. Table 2 shows the PSNR value in some wavelet and some of the test image

Table 2: PSNR results (in dB) for wavelet and Test Image

Wavelet\Image	Bridge	City	Clown
Haar	304.89	303.46	307.59
Daubechies 2	251.01	252.4	251.22
Daubechies 3	229.12	230.8	228.45
Daubechies 4	243.74	245.35	243.07
Daubechies 5	240.04	241.5	239.17
Coiflet 1	247.74	249.04	248.24
Coiflet 2	225.42	226.89	225.22
Coiflet 3	252.98	254.12	253.24
Coiflet 4	219.9	220.84	220.51
Coiflet 5	173.3	174.21	173.67
Symlet 2	251.01	252.4	251.22
Symlet 3	229.12	230.8	228.45
Symlet 4	253	254.31	253.55
Symlet 5	262.29	263.64	262.98
Symlet 6	248.86	250.16	249.4
Symlet 7	250.15	251.35	251.02
Symlet 8	260.86	262.93	259.99

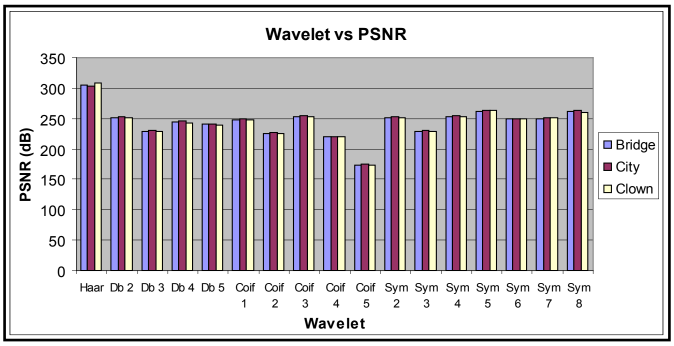

Fig. 5: Wavelet versus PSNR

In table 2 and Fig. 5, it shows that wavelet Haar has the highest PSNR for the Daubechies family, while Coiflet 3 for Coiflet family, as well Symlet 5 for Symlet family.

C. Compression ratio versus PSNR

This section analyzes two aspects of image compression, the compression ratio and PSNR, assuming both are given equal weight so that the average is visible. The test image used here is bridge.bmp that is of 512 x 512 grayscale. From the results of this analysis optimum wavelet will be obtained.

Table 3: Compression Ratio and PSNR results for wavelets and test Image (Bridge)

Wavelet	Compression Ratio (%)	PSNR (dB)
Haar	99.312	304.89
Daubechies 2	99.237	251.01
Daubechies 3	99.156	229.12
Daubechies 4	99.075	243.74
Daubechies 5	98.987	240.04
Coiflet 1	99.156	247.74
Coiflet 2	98.902	225.42
Coiflet 3	98.682	252.98
Coiflet 4	98.401	219.9
Coiflet 5	98.103	173.3
Symlet 2	99.237	251.01
Symlet 3	99.156	229.12
Symlet 4	99.075	253
Symlet 5	98.987	262.29
Symlet 6	98.902	248.86
Symlet 7	98.812	250.15
Symlet 8	98.723	260.86

1. Daubechies family

Based on table 3 and Fig. 6, it shows that wavelet Haar has a compression ratio and highest PSNR. However, when comparing the two aspects, the three top results are of Haar, Daubechies 2 and Daubechies 4.

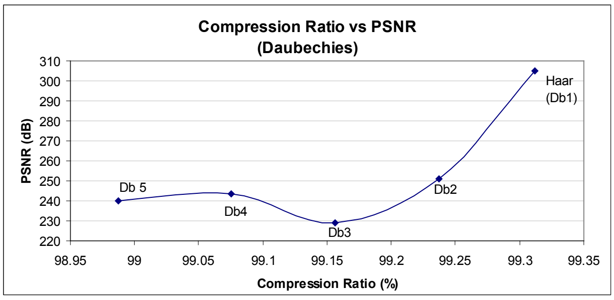

Fig. 6: Compression ratio versus PSNR (Daubechies Family)

2. Coiflet Family

From table 3 and Fig. 7, it appears that wavelet Coiflet 1 has the highest compression ratio, and Coiflet 3 has the highest PSNR. However, when comparing the two aspects, the result is as follows: Coiflet 3, Coiflet 1, and Coiflet 2.

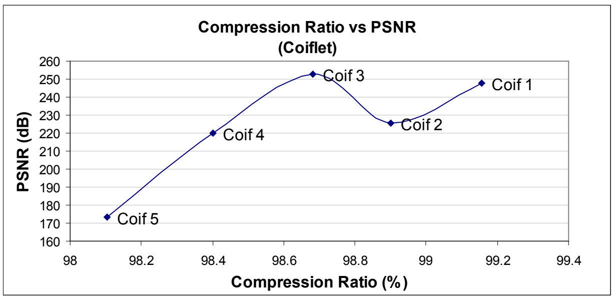

Fig. 7: Compression ratio versus PSNR (Coiflet family)

3. Symlet Family

Based on table 3 and Fig. 8, it shows that wavelet Symlet 5 has the highest PSNR, and Symlet 2 has the highest compression ratio. However, when comparing the two aspects, the three best results are Symlet 5, Symlet 8, and Symlet 4.

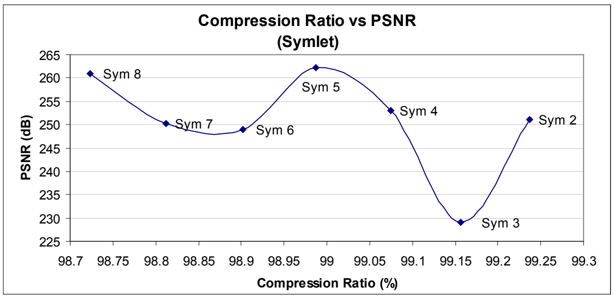

Fig. 8: Compression ratio versus PSNR (Symlet Family)

V. Conclusion

Based on the results of testing and discussion it can be drawn several conclusions:

1. Wavelet with the highest compression ratio are
 a. Haar for Daubechies family
 b. Coiflet 1 for Coiflet family
 c. Symlet 2 for Symlet family
2. Wavelet with the highest PSNR are
 a. Haar for Daubechies family
 b. Coiflet 3 for Coiflet family
 c. Symlet 5 for Symlet family
3. Wavelet with a compression ratio and the PSNR optimums are
 a. Haar, Daubechies 2 and Daubechies 4 for Daubechies family
 b. Coiflet 3, Coiflet 1, and Coiflet 2 for Coiflet family
 c. Symlet 5, Symlet 8, and Symlet 4 for Symlet family

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