Color Image Compression Using Orthogonal Wavelet Viewed From Decomposition Level and Peak Signal to Noise Ratio

Albertus Joko Santoso[1,2], Lukito Edi Nugroho[3], Gede Bayu Suparta[4], Risanuri Hidayat[5]

[1]*Currently a PhD student in the Dept. Electrical Engineering and Information Technology, Faculty of Engineering, University of Gadjah Mada Yogyakarta, Indonesia.*
[2]*Department of Informatic Engineering, Faculty of Industrial Engineering University of Atma Jaya Yogyakarta, Indonesia.*
[3,5]*Department of Electrical Engineering and Information Technology, Faculty of Engineering, University of Gadjah Mada Yogyakarta, Indonesia.*
[4]*Faculty of Mathematics and Science, University of Gadjah Mada Yogyakarta, Indonesia.*

[1,2]*albjoko@gmail.com* or *albjoko@mail.uajy.ac.id*, [3]*lukito@mti.ugm.ac.id*, [4]*gb_suparta@yahoo.com*, [5]*risanuri@te.ugm.ac.id*

Abstract

There have been substantially growing needs for storage space as there are more and more valuable and important stuff to be stored. The data which, originally, used to be processed manually and kept physically in the form of paper are now transformed into computerized data. However, these data keep increasing and within a certain period of time they become very large that they take more space to store. This situation causes serious problems in storing and transmitting image data. This research tries to find out the influence of wavelet to the Peak Signal to Noise Ratio (PSNR), and its level of decomposition towards the PSNR. The wavelet used are Daubechies family of Haar (Daubechies 1), Daubechies 2, Daubechies 3, Daubechies 4, Daubechies 5, and Coiflet families, as well as Symlet families. Test images used are 24-bit color image which are 512x512 in size. The wavelet which has the highest PSNR in each family is Haar, Coiflet 3, and Symlet 5. The effect of decomposition level towards PSNR is that the greater is the level of the decomposition, the smaller its PSNR becomes.

***Keywords**: Compression, image, wavelet, decomposition level, PSNR*

1. Introduction

The exponential development growth of the Internet and multimedia technologies results in the vast amount of information managed by computer [1]. In addition, the use of digital images is growing rapidly. This causes serious problems in the storing and transmitting image data. Management needs to consider the volume of image data storage capacity and transmission bandwidth [2]. Gibson et.al [3] warn that the digital signal requires more bits per second (bps) in both the processes of storing and delivering that result in higher costs.

Besides, the world has shifted from the industrial era into the information age. Human's need for the latest information increases in every aspect. The computer that was originally used to calculate and generate pages of reports has been abandoned. Now it generates a report which contains information that is concise and efficient. Efficient form of information is required to display something that can represent pages and pages of reports that requires large storage space and transmission bandwidth that need to be managed technically and economically [1].

The need for storage space at present has grown substantially. There is increasing number of valuable and important information to store, such as student records, population data, and others. The same thing applies in the computer world. Data which used to be originally processed manually and kept physically in the form of paper, with the use of computer began to switch to be computerized data. These data further increase and within a certain period of time they become so large that affect the storage space. Then there is a need to consider a way to compress the data so that the storage capacity needed can be smaller. When the data is needed, the user can just return the file into its 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].

At present many methods are available for data compression, one of which is with wavelet. Therefore this study is meant to find out the influence of wavelet towards the PSNR and its level of decomposition of the PSNR. The wavelet used are Daubechies family of Haar (Daubechies 1), Daubechies 2, Daubechies 3, Daubechies 4, Daubechies 5, and Coiflet families, and families Symlet. Test images used in this study are 24-bit color image in 512x512 in size.

2. Literature Review

Image compression is the application of data compression performed on the digital image in order to reduce the redundancy of the data contained in the image so that it can be stored or transmitted efficiently. 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 duplicated data. There are two duplications of data in the image. The first is the existence of a pixel that has the same intensity as its neighboring pixel, so that each pixel wastes storage space. The second is that an image contains many sections (regions) which are the same, so that these same sections need not be encoded many times to avoid redundancy.

Currently, most applications want an image representation with a minimum memory requirement. Image compression is aimed to minimize the memory requirement to represent 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 not as big as than the representation of the original image.

Image data compression can be done with wavelet transform. Wavelet is a mathematical function that divides the data into different frequency components, then study each component with a resolution suitable for any scale [5]. 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 [6] says that one of the natures of wavelet is the infrequency. In fact, there are many coefficients in the representation of wavelet whose value is zero or very small. This characteristic gives the opportunity to perform image data compression.

The main properties of wavelet transform in still image compression is the emergence of minimum distortion in the reconstructed image even though removal transform coefficients being exercised are near zero. Meanwhile, wavelet transform on an image will result in many subfield images that have very small magnitude. The determination on non-negative threshold, the elements of subfield images are very small and can be zeroed as to produce a very rare matrix. The existence of the very rare matrix will make it easier for the image to be transmitted and stored, even the result of image reconstruction with the use of threshold (quantization) can provide visual results for bare eyes.

Currently, wavelet applications have received much attention in the research world, one of which is to analyze the image. As a technique of 2-dimensional discrete signal analysis, for example images, wavelet decomposes signal into average signal, vertical, horizontal and diagonal details 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 with the Discrete Wavelet Transform [7] or the standard decomposition techniques and non-standard with wavelet Haar ([8], [9]). Feature image generated by wavelet is taken from a wavelet coefficient at a certain level (example 3, 4 or 5) and reduced to a smaller image.

In the wavelet transform process for 2-dimensional image, there are two ways to decompose the pixel values, the standard decomposition and nonstandard decomposition [6]. Each method is obtained based on wavelet transform 1-dimensional.

In standard decomposition process of an image, first a wavelet transform 1-dimensional image is used on each row. This process will generate a mean value along with detail coefficients for each row. Then wavelet transform 1-dimensional image is applied on each column. The result of this process is in the form of detail coefficients and one coefficient average.

Figure 1. Standard Decomposition of an Image (Transform rows)

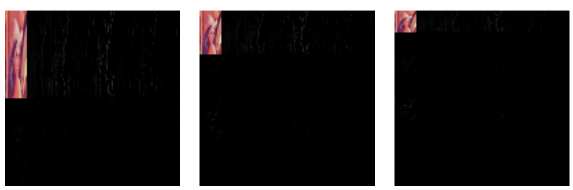
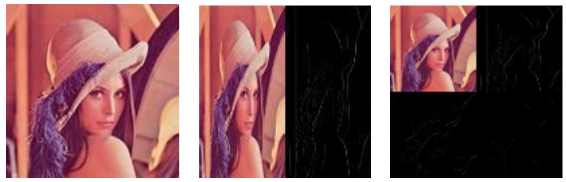


Figure 2. Standard Decomposition of an Image (Transform columns)

Non-standard decomposition transformation is obtained by combining pairs of rows and columns transformation alternately. In the first step applied to wavelet transform 1-dimensional row, then applied a wavelet transform 1-dimensional column.



(a) (b) (c)

Figure 3. Non-standard Decomposition of an Image
(a). Original image,
(b). Decomposition of the row
(c). Decomposition of the column

In the decomposition level 1, the image will be divided into 4 sub bands, called HH, HL, LH, and LL. The HH sub band image gives details on the diagonal, the HL provides detailed images in the horizontal direction, while the LH provides vertical detailed images. 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 in accordance with the desired level.

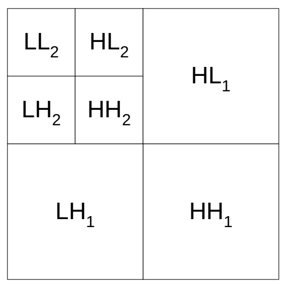


Figure 4. Image Decomposition

In the discrete wavelet transform (DWT) there are properties for precise reconstruction. This nature gives a sense that in fact no information is lost after the transformed image is set to its original form. But there are missing information on image data compression with wavelet transform that occurs during quantization.

Information loss due to compression should be minimized to keep the quality of the compression. Compression quality is usually inversely proportional with the memory requirement. A good quality compression is generally achieved in the process of memory consolidation, which generates a small reduction, and vice versa. In other words, there is reciprocal (trade off) between image quality and the size of the compression. The quality of an image is subjective and relative, depending on the observation of the user. One can only say the quality of a good image, but others may disagree. There are two things that can be used as benchmarks of compression quality, the PSNR and compression ratio.

PSNR (Peak Signal to Noise Ratio) 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 images with the original image. A larger PSNR produces better image quality. PSNR equation is illustrated below:

$$PSNR = 20x\log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \qquad (1)$$

where

$$MSE = \frac{1}{mn}\sum_{y=1}^{m}\sum_{x=1}^{n}(I(x,y) - I'(x,y))^2 \qquad (2)$$

3. Research Methodology

This research employs 17 wavelet, namely Daubechies families (Haar, Daubechies 2, Daubechies 3, Daubechies 4 and Daubechies 5), family Coiflet (Coiflet 1, Coiflet 2, Coiflet 3, Coiflet 4, and Coiflet 5), and family Symlet (Symlet 2, Symlet 3, Symlet 4, Symlet 5, Symlet 6, Symlet 7, Symlet 8). The test images used are in the form of 24-bit color images, namely lena.bmp, pepper.bmp, sarijana.bmp, and teko.bmp with size 512 x 512. The test images can be seen in Figure 5.

(a) **(b)** **(c)** **(d)**

Figure 5. Test Images, (a). Lena, (b). Pepper, (c). Sarijana, (d). Teko

All test images were examined for image compression with the use of wavelet, so that the value of PSNR for each image on every wavelet used for testing is known. The diagram of the testing process of image compression and image reconstruction can be seen in Figure 6. 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.

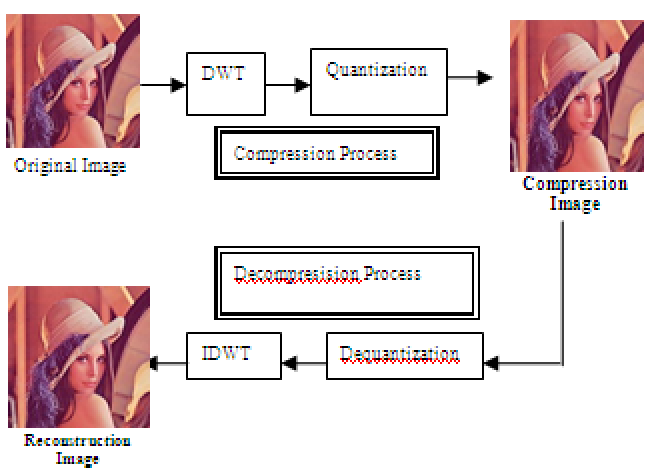


Figure 6. Compression and Decompression Process

4. Results and Discussion

This paper presents some results of the programs compiled with the help of MATLAB. In addition, this study also presents test results on a wavelet influence towards PSNR, and the influence of decomposition level towards PSNR with several types of wavelet, namely Haar, Daubechies 2, Daubechies 3, Daubechies 4, Daubechies 5, family Coiflet, and family Symlet.

4.1.The influence of Wavelet on PSNR

PSNR is used to quantify the image quality. When the PSNR value is higher, the wavelet functions better, this means that the reconstructed image is likely to be the same as the original image. Table 1 shows the PSNR value in some wavelet and some of the test image.

Table 1. PSNR Results (in dB) for Wavelet and Test Images

Wavelet\Image	Lena	Pepper	Sarijana	Teko
Haar	304.4	305.3033	304.5467	306.02
Daubechies 2	253.04	252.09	249.6167	254.99
Daubechies 3	230.2267	228.85	228.0467	232.0533
Daubechies 4	244.8567	243.49	242.65	246.67
Daubechies 5	240.8333	239.4133	238.8767	242.7
Coiflet 1	250.0233	249.36	246.1033	252.0167
Coiflet 2	227.0267	225.92	224.2267	228.88
Coiflet 3	255.69	254.6433	251.73	257.5267
Coiflet 4	222.7067	221.9467	218.7467	224.6733
Coiflet 5	175.9633	175.28	172.1367	177.9167
Symlet 2	253.04	252.09	249.6167	254.99
Symlet 3	230.2267	228.85	228.0467	232.0533
Symlet 4	255.33	254.7433	251.39	257.3467
Symlet 5	264.7033	264.1867	260.6167	266.76
Symlet 6	251.1767	250.4767	247.38	253.1733
Symlet 7	252.8	252.2767	248.3567	254.8833
Symlet 8	261.7933	260.34	259.7033	263.6

While the results from testing a wavelet influence on PSNR for several test images can be seen in figure 7 to figure 9.

4.1.1. Daubechies family: Based on table 1 and figure 7, it shows that the wavelet Haar has the highest PSNR value, while the wavelet Daubechies 3 has the lowest. When viewed from the test image, the one which has the highest PSNR is teko.bmp test images. Test images of teko.bmp have the highest PSNR value because it has a distribution of colors of constant degradation. This is the differentiating factor compared to the other test images.

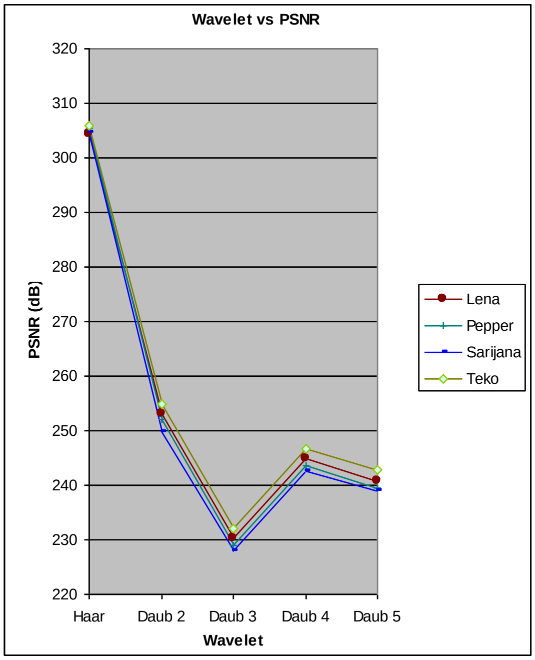


Figure 7. Wavelet versus PSNR (Daubechies Family)

4.1.2. Coiflet Family: In table 1 and figure 8, it appears that wavelet Coiflet 3 has the highest PSNR, while the wavelet Coiflet 5 has the lowest PSNR. When viewed from the test image, the one that has the highest PSNR is that of teko.bmp test images.

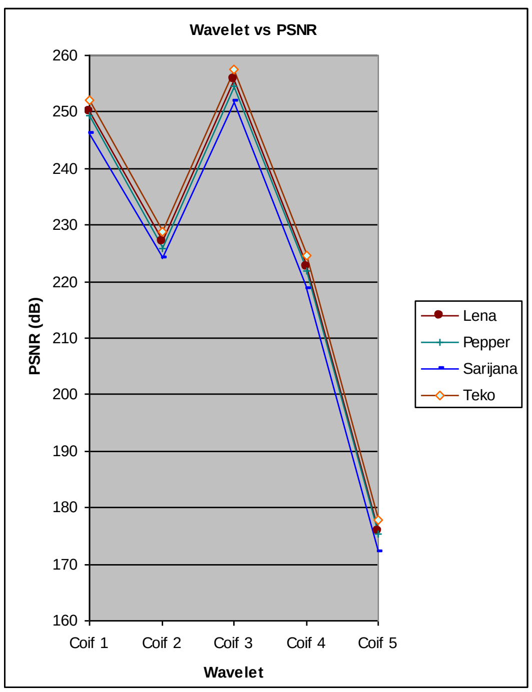


Figure 8. Wavelet versus PSNR (Coiflet Family)

4.1.3. Symlet Family: Based on table 1 and figure 9, it shows that wavelet Symlet 5 has the highest PSNR, while the wavelet Symlet 3 has the lowest. When viewed from the test image, the one with the highest PSNR is of teko.bmp.

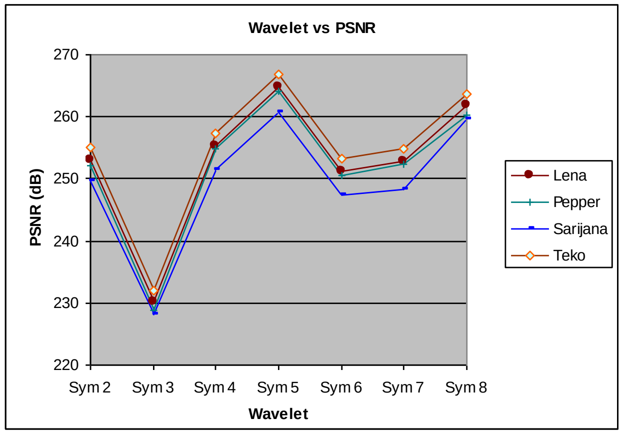


Figure 9. Wavelet versus PSNR (Symlet family)

4.2. The Influence of Decomposition Level on the PSNR

This test aims to determine the influence of decomposition level on PSNR of the tested wavelet bands. Testing was conducted at several levels of decomposition, starting level 1 to level 8. Test images used are Lena.bmp. The decomposition level test results on PSNR for several wavelets can be seen in tables 2-4 and figures 10-12.

4.2.1. Daubechies family: Tests on Daubechies family only for Haar (Db 1), Db 2, Db 3, Db 4, and Db 5. Test results can be seen in table 2 and figure 10.

Table 2. PSNR results (in dB) for Wavelet and Decomposition level (Daubechies Family)

Wavelet\Level	1	2	3	4	5	6	7	8
Haar (Db 1)	316.0667	310.4367	307.09	304.4	302.7833	301.3	300.06	298.9333
Daubechies 2	266.6067	260.1133	256.09	253.04	250.5433	248.4433	246.94	245.9733
Daubechies 3	243.79	237.35	233.2533	230.2267	227.8567	226.1233	224.9733	224.56
Daubechies 4	258.7433	252.1	247.9267	244.8567	242.4567	240.67	239.4633	238.9533
Daubechies 5	255.06	248.2533	243.9867	240.8333	238.4667	236.75	235.69	235.1633

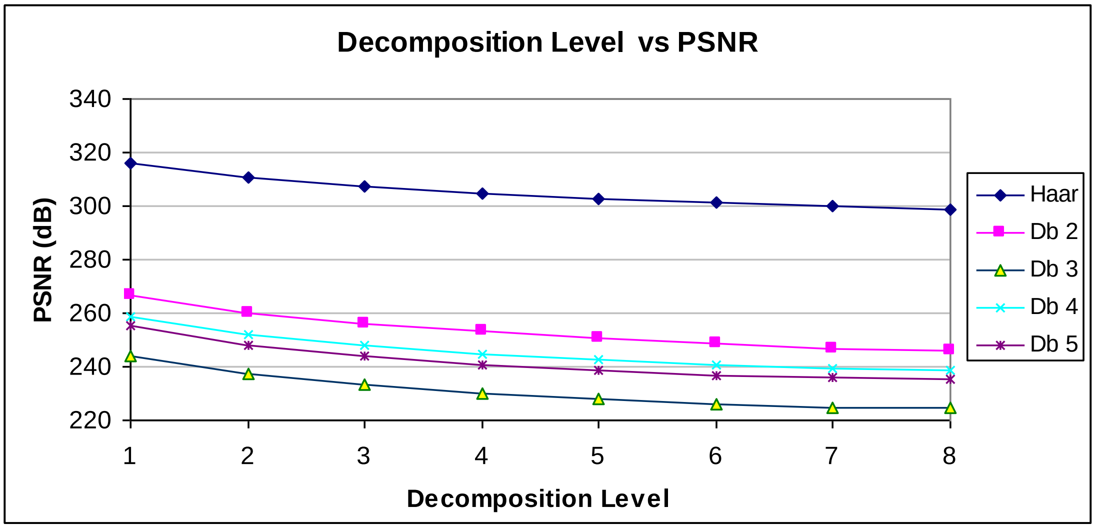


Figure 10. Decomposition Level versus PSNR (Daubechies Family)

Based on table 2 and figure 10, it shows that the greater the level of decomposition is, the smaller is the PSNR value. It means that the larger value of the level of decomposition leads to the greater difference between the original images from the reconstructed image. Haar wavelet has the highest PSNR value for each level of decomposition.

4.2.2. Coiflet Family: The results of testing determine the influence of decomposition level towards PSNR on Coiflet family can be seen in Table 3 and Figure 11.

Table 3. PSNR Results (in dB) for Wavelet and Decomposition Level (Coiflet Family)

Wavelet\Level	1	2	3	4	5	6	7	8
Coif let 1	262.6633	256.6767	252.9767	250.0233	247.6833	245.6233	244.2733	243.56
Coif let 2	241.1767	234.3533	230.1533	227.0267	224.57	222.6033	221.35	220.74
Coif let 3	266.2133	261.5733	258.26	255.69	253.79	252.55	252.2833	252.2933
Coif let 4	233.66	228.8767	225.4133	222.7067	221.0533	220.24	220.2167	220.1867
Coif let 5	186.8667	182.1667	178.79	175.9633	174.5267	174.3	174.2667	174.2233

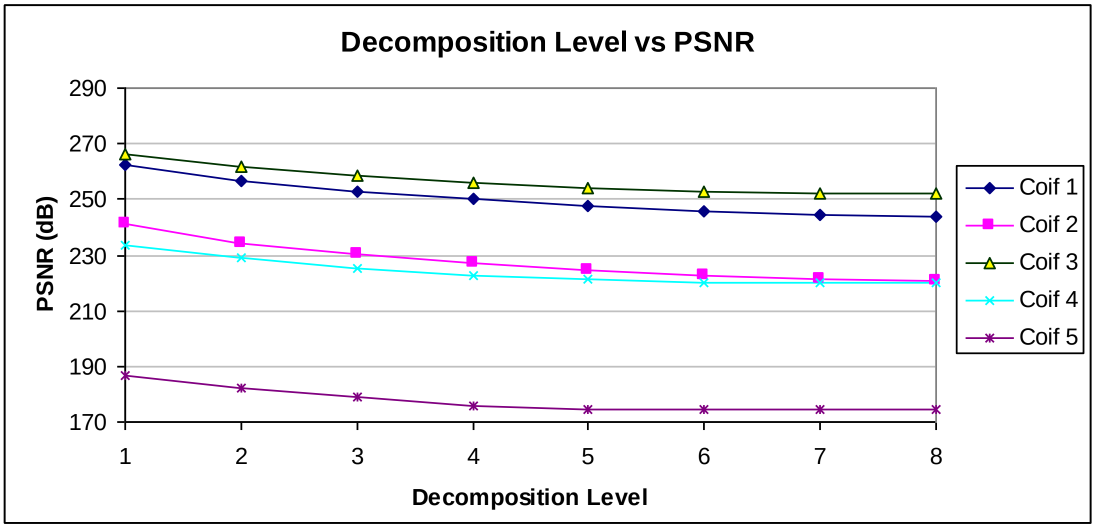


Figure 11. Decomposition Level versus PSNR (Coiflet Family)

In Table 3 and Figure 11, it shows that the greater the level of decomposition is, the smaller is its PSNR value. The wavelet Coiflet 3 has the highest PSNR value for each level of decomposition.

4.2.3. Family Symlet: The results of testing determine the influence of decomposition level towards PSNR on Symlet family can be seen in table 4 and figures 12.

Table 4. PSNR Results (in dB) for Wavelet and Decomposition Level (Symlet Family)

Wavelet\Level	1	2	3	4	5	6	7	8
Symlet 2	266.6067	260.1133	256.09	253.04	250.5433	248.4433	246.94	245.9733
Symlet 3	243.79	237.35	233.2533	230.2267	227.8567	226.1233	224.9733	224.56
Sym et 4	267.9733	261.9233	258.2533	255.33	253.0033	250.9267	249.56	248.85
Symlet 5	276.9567	271.0467	267.4967	264.7033	262.3867	260.3167	258.88	258.0633
Symlet 6	264.12	257.98	254.15	251.1767	248.7833	246.6967	245.3233	244.5833
Symlet 7	263.7667	258.65	255.4033	252.8	250.54	248.64	247.3333	246.6733
Symlet 8	273.1167	268.0167	264.46	261.7933	259.6233	258.2033	257.33	257.16

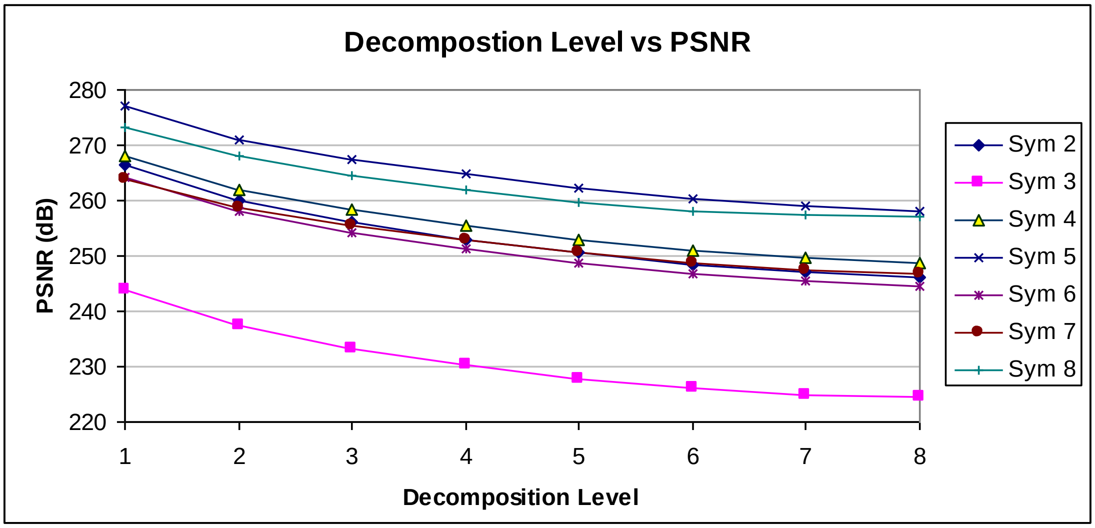


Figure 12. Decomposition Level versus PSNR (Symlet Family)

Based on table 4 and figures 12, it shows that the greater the level of decomposition is, the smaller is its PSNR value. Symlet 5 has the highest PSNR value for each level of decomposition.

5. Conclusion

Based on testing results, it can be concluded that the wavelet Haar, Coiflet 3, and Symlet 5 have the highest PSNR value in every family. The influence of decomposition level versus PSNR is that the greater level of decomposition is, the smaller is its PSNR value.

References

[1] Tan, C.L., *Still Image Compression Using Wavelet Transform*, The University of Queenslands, 2001.

[2] Talukder, K.,H., dan Harada, K., *Haar Wavelet Based Approach for Image Compression and Quality Assessment of Compresed Image*, IAENG International Journal of Applied Mathematics, 36:1, IJAM_36_1_9, 2007.

[3] Gibson, J., D., Berger, T., Lookabaugh, T., Linbergh, D., dan Baker, R.,L., *Digital Compression for Multimedia*, Morgan Kaufman Publishers, Inc. San Fransisco, California, 1998.

[4] Effelsberg, W., dan Steinmetz, R., *Video Compression Technique*, Dpunkverlag for digitale Technologie, Muthig GMBH, Jerman, 1998.

[5] Mubarak, R., *Pemampatan Data Citra Dengan Menggunakan Transform Gelombang-Singkat*, UGM, Yogyakarta, 2003.

[6] Stollnitz, E.J, DeRose, T.D., dan Salesin, D.H., *Wavelets For Computer Graphics: Theory and Applications*, Morgan Kaufman Publisher, USA, San Fransisco, 1996.

[7] Mallat, S, *A Wavelet Tour Of Signal Processing*, Academic Press, USA, 1999.

[8] Chakrabarti,K., Garofalakis, M., Rastogi, R., dan Shim, K., *Approximate Query Processing Using Wavelet*, Proceedings of the 26th VLDB Coference, Cairo, Egypt, 2000.

[9] Natsev, A., Rastogi, R., dan Shim, K., *Walrus: A Similarity Retrieval Algorithm For Image Databases*, Duke University and Bell Laboratories, USA, 1999.

Authors

Albertus Joko Santoso is a lecturer at Department of Informatics Engineering, Faculty of Industrial Engineering University of Atma Jaya Yogyakarta, Indonesia. Currently a PhD student in Department of Electrical Engineering and Information Technology, Faculty of Engineering, Gadjah Mada University, Indonesia. He holds a M.S. degree and a B.S. degree in Electrical Engineering from Gadjah Mada University Indonesia. He is a member of the IAENG (International Association of Engineer) and the CSTA (Computer Science Teachers Association). His research interests are image processing, artificial intelligence, data mining, wavelet and computation.

Lukito Edi Nugroho is a lecturer at Department of Electrical Engineering and Information Technology, Faculty of Engineering, Gadjah Mada University, Indonesia. He holds a Ph.D. degree in mobile computing from school of Computer Science and Software Engineering at Monash University Australia, a M.S. degree in computer science from James Cook University of North Queensland Australia, and a B.S. degree in electrical engineering from Gadjah Mada University Indonesia. His research interests are in mobile computing, software engineering and information systems.

Gede Bayu Suparta is an A/Professor in the Department of Physics, Faculty of Mathematics and Science, Gadjah Mada University. Current research interest is know science, learn engineering, create technology, develop business.

Risanuri Hidayat received the B.S. degree in Electrical Engineering from Gadjah Mada University Indonesia in 1992. He received M.Sc. degree in Information Communication Technology from Agder University College Norway in 2002 and D.Eng degree from Department of Electrical Engineering Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang (KMITL) Bangkok, Thailand. He has been member of the Department of Electrical Engineering and Information Technology, Gadjah Mada University. His research interest is in signal processing, and communication systems.