

## KORESPONDENSI

JOIV : International Journal on Informatics Visualization

<https://joiv.org/index.php/joiv/index>

Scopus Q3

Title: "**Comparison of the Packet Wavelet Transform Method for Medical Image Compression**"

Authors: **I Made Ari Dwi Suta Atmaja, Wilfridus Bambang Triadi, I Nyoman Gede Arya Astawa, Made Leo Radhitya**





I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

---

## [JOIV] Submission Acknowledgement

---

Rahmat Hidayat &lt;joiv@pnp.ac.id&gt;

Sun, Apr 2, 2023 at 4:04 PM

To: I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

I Nyoman Gede Arya Astawa:

Thank you for submitting the manuscript, "Comparison of the Packet Wavelet Transform Method for Medical Image Compression" to JOIV : International Journal on Informatics Visualization. With the online journal management system that we are using, you will be able to track its progress through the editorial process by logging in to the journal web site:

Manuscript URL: <http://joiv.org/index.php/joiv/author/submission/1732>

Username: aryaastawa

If you have any questions, please contact me. Thank you for considering this journal as a venue for your work.

In addition, due to the rising costs of academic publications, starting 2021, publication fees shall be implemented to all accepted papers. For more details, please email to joiv [at] [pnp.ac.id](http://pnp.ac.id). This journal charges the following author fees (Article Publication Fee):

- Indonesian authors: 3.500.000 IDR per article (Regular)
- Indonesian authors: 5.000.000 IDR per article (Fast Track)
  
- International authors: 280 USD per article (Regular)
- International authors: 400 USD per article (Fast track)

This fee includes:

- DOI registration for each paper
- Checking the article similarity by turnitin
- English proofreading

For hardcopy, the fee (excluding postage and handling cost) is 500.000 IDR per issue.

If the manuscript is accepted for publication, you will be asked to pay an Article Publication Fee to cover publications costs. This charge is for the first 10 pages, and if any published manuscript over 10 pages will incur extra charges 50 USD per page.

Best regards,

Rahmat Hidayat  
JOIV : International Journal on Informatics Visualization

---

<http://joiv.org/index.php/joiv>



I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

---

## [JOIV] Editor Decision

---

**Alde Alanda** <aldealanda@gmail.com>

Wed, May 10, 2023 at 10:13 AM

To: I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

I Nyoman Gede Arya Astawa:

We have reached a decision regarding your submission to JOIV : International Journal on Informatics Visualization, "Comparison of the Packet Wavelet Transform Method for Medical Image Compression".

Our decision is: Revisions Required

== initial review==

The word number in abstract should be within 230-250 words and consists of objectives, materials, method, results, and implication for further research.

All the citations should be listed in the references. It is expected that the citations are at least 30 sources, and 70% are the publication within 2017-2022

Alde Alanda  
(Scopus ID: 57203718850); Politeknik Negeri Padang, Sumatera Barat  
Phone 81267775707  
Fax 81267775707  
[aldealanda@gmail.com](mailto:aldealanda@gmail.com)

Alde Alanda

---

<http://joiv.org/index.php/joiv>



I Nyoman Gede Arya Astawa <arya\_kmg@pnb.ac.id>

---

## [JOIV] Editor Decision

---

**I Nyoman Gede Arya Astawa** <arya\_kmg@pnb.ac.id>  
To: Alde Alanda <aldealanda@gmail.com>

Thu, May 18, 2023 at 4:34 PM

dear, Alde Alanda

We have made improvements according to the suggestions, the improvements are:

1. The number of words in the abstract has been fixed
2. Citations have been added (more than 30 sources) and publication in the period 2017-2022

Thank You

salam

Dr. I Nyoman Gede Arya Astawa, ST., M.Kom

(Komang Arya)

Politeknik Negeri Bali

Jurusan Teknik Elektro

Prodi Manajemen Informatika

Telp: 08123814894

[Quoted text hidden]



**JOIV-I Made Ari Dwi Suta Atmaja-medis.docx**  
1026K

# Comparison of the Packet Wavelet Transform Method for Medical Image Compression

I Made Ari Dwi Suta Atmaja<sup>a\*</sup>, I Nyoman Gede Arya Astawa<sup>b</sup>, Wilfridus Bambang Triadic<sup>c</sup>, Made Leo Radhitya<sup>d</sup>

<sup>a b</sup> Department of Electrical Engineering, Politeknik Negeri Bali, Badung, 80361, Indonesia

<sup>c</sup> School of Computer Sciences, Universiti Sains Malaysia, Malaysia

<sup>d</sup> Department of Informatics, STMIK STIKOM Indonesia, Denpasar, Bali, 80225, Indonesia

\*Corresponding author: arisuta@pnb.ac.id

**Abstract**— Medical images are often used for the purposes of learning, analysis, and medical diagnosis. Medical image data requires a large amount of storage on a computer. The type of wavelet chosen in this study is the type of wavelet that is often used by researchers, namely haar, daubechies, and biorthogonal wavelets. This study aims to find the best wavelet method out of the three tested wavelet methods (Haar, Daubechies, and Biorthogonal). The test was carried out by comparing the compression ratio, compression, and decompression time for each medical image. There are three threshold values used, namely 30, 40, and 50. This study uses medical images that represent types of ultrasound and CT-scan images as testing data. The results of the first test for the compression ratio on both medical images showed that CT-scan images on Haar and biorthogonal wavelets were the best with an average compression ratio of 40.76%, and PSNR of 33.77, and a compression time of 0.19 seconds and an RLE decoding time of 0.65 seconds. The second test is for compression time on all wavelet methods, CT-scan medical images have the fastest compression process. The last test for the fastest decompression time occurs in the Haar wavelet for CT-scan images as fast as 0.65 seconds, while the longest occurs in the Daubechies wavelet on USG images as fast as 1.08 seconds. Based on the test results, this study recommends that the Haar wavelet method is very good for compressing and decompressing medical images, such as CT-scan images.

**Keywords**— Medical Image; wavelet; Haar; Daubechies; Biorthogonal

*Manuscript received 15 Oct. 2020; revised 29 Jan. 2021; accepted 2 Feb. 2021. Date of publication 17 Feb. 2021. International Journal on Informatics Visualization is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.*



## I. INTRODUCTION

Medical images are often used for learning, analysis, and medical diagnosis [1] so in the field of medical education, medical images play a very important role [2]. According to researchers [3], a medium-sized hospital alone currently produces an average of 5GB to 15GB of data. This will cause difficulties for hospitals to handle such large data, both in storage and in sending image data. Images that have a large capacity require a long time to be sent [4], so the desire to get fast information cannot be accommodated properly. One solution to this problem is image compression [1].

Image compression is a method that aims to reduce memory usage [5], making it easier to store. Processing and transmitting digital data will require a shorter time than

uncompressed data [6]. There are many methods for image compression today. In general, compression methods are divided into two types: lossy and lossless [7, 8]. Lossy compression usually has a good ratio, but the resulting image quality is lower due to missing information from the original image [7, 9-11]. Lossless compression is a compression technique with the quality of the reconstructed image being the same as the original image, but in most natural images it produces a bad ratio [5, 7, 8, 12].

When compressing an image, there are two parameters that must be measured, namely the compression ratio and the decompressed image quality. A good method for compression is one that is capable of producing a high compression ratio, but the resulting reduction in image quality is still tolerated by the human eye [6, 13]. Besides, when the compression method is applied, we cannot let go of the decompression process. A

medical image is an image that will be analyzed and used by doctors, thus the quality of the reconstructed medical image must not decrease and is still acceptable. There are several studies related to medical image compression, such as those carried out by [5, 14-16]. The number of studies on medical image compression at present shows that this problem is a concern for many researchers in the world. Based on these data, a good compression method is needed. This research concerns medical image compression by applying wavelet packet transform (PWT) and lossless RLE coding to maintain good image quality.

The basic principle of PWT is to obtain a time and scale representation of a signal using digital filter techniques and sub-sampling operations. The wavelet transform uses two important components in the process, namely, scaling (scaling function) or low-pass filtering and wavelet (wavelet function) or high-pass filtering. Several studies such as [16, 17] show that wavelets can provide good image quality with high compression ratios. Wavelet techniques usually use the discrete wavelet transform (DWT), where only low-frequency elements are decomposed deeper, while high-frequency elements are not decomposed any further. This study decomposes each element, both low and high frequency, using wavelet packet transform (PWT). The fundamental difference between DWT and PWT is that PWT does not only decompose low frequency elements but also high-frequency elements. This is also an advantage of PWT compared to DWT [18]. The resulting ratio will be regulated with the provision of a threshold. According [18], a good ratio can be obtained by providing an appropriate threshold.

The Run Length Encoding (RLE) compression technique has been widely used. This method utilizes the repetition of pixel values that occur sequentially. In addition, RLE works well on data that has a large number of data repetitions [19]. RLE is a lossless compression method that will maintain the original quality of data both before and after compression [20, 21]. So, this method will work well when combined with wavelet transformation on medical images. This combination makes no data lost. Research that has been done for image compression with RLE, was carried out by [5] who used Enhanced RLE, by modifying ordinary RLE, which aims to produce a perfect image reconstruction ratio.

The PWT method used in this research is to perform image decomposition at low and high frequencies. This decomposition makes it possible to store all image features and finally, the ratio can be controlled by threshold and combining it with RLE. The novelty of this medical image compression research is finding one of the best wavelet methods out of the three tested wavelet methods (Haar, Daubechies, and Biorthogonal). Tests were carried out on the three wavelets to produce a high compression ratio with good decompressed image quality.

## II. MATERIAL AND METHOD

There are several stages in medical image compression research as shown in Figure 1. The first process is to insert medical images from CT-scan images or ultrasound images. The second process is compression using the haar, Daubechies, and biorthogonal wavelet methods, where in this study the decomposition level will be selected by the user. The results of the decomposition in matrix form are given a

threshold and data that has a value below the threshold is changed to zero. The results of this decomposition are encoded using RLE with the hope that the data representation can be shorter so that the compression ratio can be increased without reducing image quality. RLE code that has been built, and stored in a file. The decompression process is done by opening the file that contains the RLE code data. Then read the data to return the data with RLE decoding. RLE decoding produces data that is reconstructed with inverse wavelet (IW). The results of this reconstruction are presented to the user as a decompressed image. In this study, data compression is the process of reducing the number of bits in data, while data decompression is the process of returning compressed data to its original form.

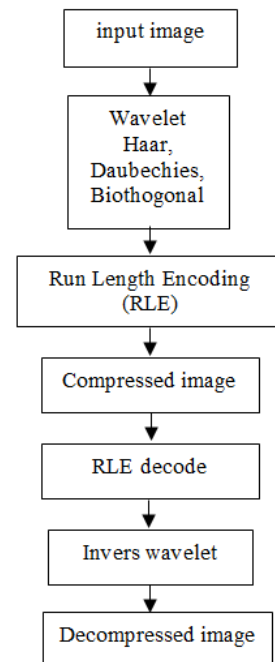


Fig 1. System flow chart

### A. Wavelet

In the wavelet transform, digital filtering techniques are used to get a depiction of a digital signal's time scale [22]. Broadly speaking, the process in this technique is to pass the signal to be analyzed on a filter with different frequencies and scales. Filterization itself is a function used in signal processing. Wavelets can be realized using filter iterations with scaling. The resolution of the signal, which is the average of the amount of detailed information in the signal, is determined through this filtration, and the scale is obtained by upsampling and downsampling [23].

The selection of wavelets in this study is based on several considerations: first, the wavelet transform can be performed perfectly with linear time. Second, practically speaking, the wavelet coefficients are mostly small or zero. This condition is very beneficial, especially in the field of data compression. Finally, wavelets are adaptable to many types of functions, such as discontinuous functions, and functions defined in a bounded domain.

The type of wavelet chosen in this study is the type of wavelet that is often used by researchers, namely haar, daubechies, and biorthogonal wavelets.

### B. RLE and RLE Decode

In data compression, there are two types of methods: lossless and lossy compression [24]. Run Length Encoding (RLE) belongs to one of the simplest lossless types of data compression schemes and is based on the simple principle of data encoding [25]. The RLE method is very suitable for compressing data containing repeated characters. The working system using the RLE (Run Length Encoding) method is as follows: (1) RLE works by reducing the physical size by repeating a string of characters/data bits; (2) This looping string is called RUN and is usually encoded in 2 bits. The first bit is the number of repetitions and the second bit is the repeated character [26].

Run Length Encoding (RLE) is done by counting the number of occurrences of a value in a certain sequence. In this method, each value will be written first [27]. If all values have been written, it will be followed by the frequency of occurrence of each value. The process of decoding the results of the RLE is carried out by writing the value of the number of times it appears. The result is an  $m \times n$  matrix based on the data stored in the file being read.

### C. Inverse wavelet

This study uses wavelets as a first step to decompose images at both low and high frequencies. This first step corresponds to the final step of the wavelet inverse. Wavelet decomposes the image by downsampling, and vice versa, the inverse reconstructs the image by upsampling [28]. All wavelet and inverse wavelet steps were carried out in this study. The process of inverse wavelet transformation or often also called the process of reconstruction of the matrix, so that a value is generated for the output image.

### D. Thresholding

Thresholding is a method of image segmentation in which the process is based on differences in the degree of the grayness of the image. In this process, it takes a limit value called the threshold value. The thresholding stage is carried out to reduce data that is considered insignificant, namely data below a certain threshold [29]. All values below the threshold will be set to zero. In this study, to test the compression ratio and image quality, several threshold values were used.

### E. Testing

Medical image quality testing uses the Peak Signal-To-Noise Ratio (PSNR) [22, 30]. The PSNR calculation will begin by finding the Mean Square Error (MSE) value with equation 1, then processing it with the PSNR calculation in Equation 2. The PSNR value for lossy compression is 30 to 50 dB [26]. The equation for calculating MSE is as follows:

$$MSE = \frac{1}{MN} \sum_{i=1}^N \sum_{j=1}^M (f_{ij} - f'_{ij})^2 \quad (1)$$

Where  $f_{ij}$  is the original image,  $f'_{ij}$  is the decompressed image,  $M$  and  $N$  are the image dimensions  
Meanwhile PSNR is calculated in the following way:

$$PSNR = 20 \times \log_{10} \left( \frac{b}{MSE} \right) \quad (2)$$

The medical images tested were two types of gray medical images, namely CT-scan images and ultrasound images. This study used threshold values of 30, 40, and 50. The test results are recorded in the compression ratio, PSNR, compression time, and decompression time table. The final results shown are in the form of average time, compression ratio and PSNR of all test images. The compression ratio is calculated using equation 3.

$$Ratio = \frac{(original\ image - compressed\ image)}{original\ image} \quad (3)$$

According to [26], image quality is considered low if the PSNR value is less than 30dB and image quality is considered high if the PSNR value is above 40dB. Meanwhile, if the PSNR value is between 30dB and 40dB, then the image quality is still acceptable.

### F. Rate Distortion

Rate distortion is concerned with the representation of the source with the smallest possible bit value for a particular desired quality [31]. Source data for rate-distortion can be images, videos, or text files. Each different source will have its own technique for representing its distortion rate, for example, voice data will be different from video data.

### G. Bit rate

Bit rate is the average bit required to represent a pixel in an image [32]. The equation that shows the bit rate value is shown in Equation 4.

$$Bit\ rate = \frac{J_s}{I_s} \text{ bpps} \quad (4)$$

Where  $J_s$  is the compressed image file size, while  $I_s$  is the number of pixels in an image. The unit of bit rate is bits per pixel (bpps).

## III. RESULT AND DISCUSSION

This study used images from two medical devices, 15 ultrasound images and 15 X-ray images. Both image files use bitmap format. Medical image testing is carried out by testing the image ratio, image quality, and compression time on three types of wavelets, namely Haar, Daubechies, and Biorthogonal.

Figure 2. Shows the test image used in the study. The test images displayed are only four of the 30 test images. Each test image has a different file capacity. Figures 2a and 2c represent X-ray test images while Figures 2b and 2d represent ultrasound test images.

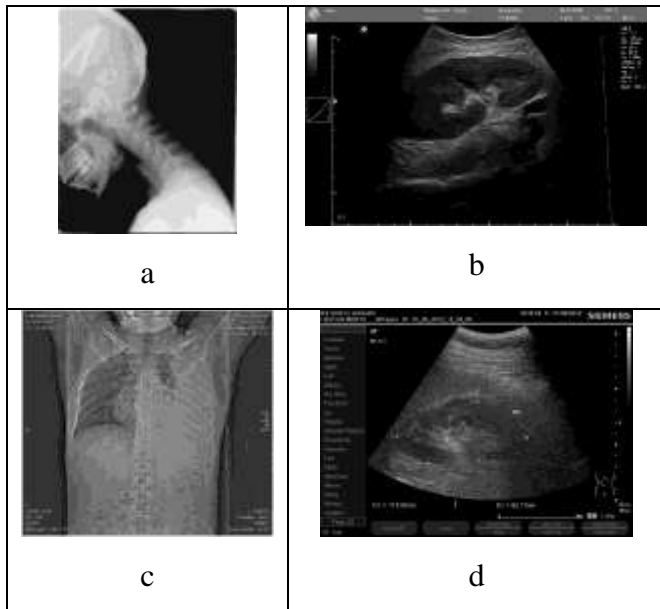


Fig. 2 (a) test image 1, (b) test image 2, (c) test image 3, (d) test image 4

Based on figure 2, image processing is carried out using the Haar, Daubechies, and Biorthogonal wavelet methods. Image data processing is done by testing each image and the results are recorded in the table. The average test results as shown in the table. The results of the first test, namely testing the compression ratio of two types of medical images on the three types of wavelet method with a threshold of 30, 40, and 50 are shown in Table I.

TABLE I.  
RATIO TEST RESULTS

| Wavelet | Threshold | CT-scan images | USG images |
|---------|-----------|----------------|------------|
| Haar    | T30       | 35,69%         | 30,36%     |
|         | T40       | 41,57%         | 39,58%     |
|         | T50       | 45,01%         | 45,56%     |
| Db      | T30       | 22,69%         | 9,21%      |
|         | T40       | 29,59%         | 22,51%     |
|         | T50       | 36,24%         | 31,48%     |
| Bi      | T30       | 35,69%         | 30,36%     |
|         | T40       | 41,57%         | 39,58%     |
|         | T50       | 45,01%         | 45,56%     |

Table I explains that of all compressed image tests it worked well. The increase in the threshold was tested on CT-scan images and ultrasound images. The test results show that the higher the threshold, the higher the compression ratio percentage. This can happen because the larger the threshold, the more information is cut and the value is changed to zero, so that the storage memory can be reduced and the image quality decreases. At all thresholds, the resulting ratio of the daubechies wavelet is quite low, compared to the ratio produced by the Haar and Biorthogonal wavelets. The best compression ratio is obtained at a threshold of 50.

TABLE II  
PSNR TEST RESULTS

| Wavelet | Threshold | CT-scan images | USG images |
|---------|-----------|----------------|------------|
| Haar    | T30       | 34,94          | 33,22      |
|         | T40       | 33,63          | 31,82      |
|         | T50       | 32,74          | 30,69      |
| Db      | T30       | 23,08          | 32,48      |
|         | T40       | 22,97          | 31,12      |
|         | T50       | 22,78          | 30,01      |
| Bi      | T30       | 34,94          | 33,22      |
|         | T40       | 33,63          | 31,82      |
|         | T50       | 32,65          | 30,69      |

The results of the second test are to determine the quality of medical images using the PSNR shown in Table II. The results are different from the first test where the greater the threshold on each wavelet, the lower the PSNR value. This decrease in PSNR occurs in both types of medical images. PSNR values vary from 22 to 35. For Haar and Biorthogonal wavelets, the resulting PSNR is still above 30, while for Daubechies wavelets on ultrasound images, the results are above 30, while on CT-scan images it is below 30 and according to [26] it's still acceptable. To determine the relationship between the ratio and the resulting PSNR, a distortion rate graph will be displayed for each test image as shown in Figure 3 and 4.

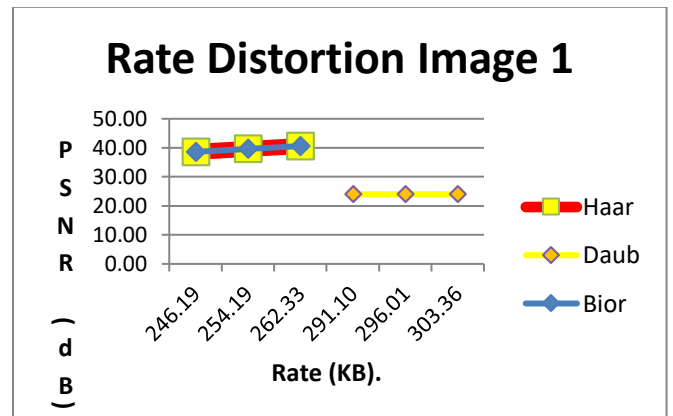


Fig. 3 Rate Distortion in test image 1

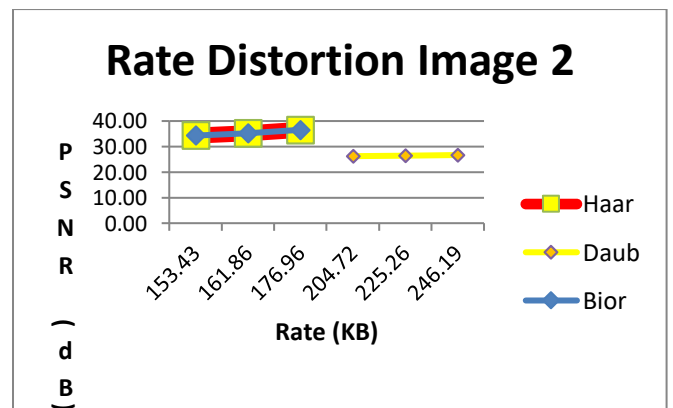


Fig. 4 Test Image Distortion Rate 2



Figures 3 and 4 show the distortion rate graphs for test image 1 and test image 2, where the x-axis shows the rate. The y-axis shows the PSNR. The graph shows that the PSNR value when using the Daubechies wavelet is lower than when using the Haar wavelet and Biorthogonal wavelet. This could be due to the fact that the Haar wavelet and Biorthogonal wavelets are more squares in shape than the Daubechies wavelets which tend to be sharp. This difference causes Haar wavelets to be more capable of producing good-quality filters for two-dimensional objects. Meanwhile, in terms of the resulting rate, the rate generated by Haar and Biorthogonal is lower than that of Daubechies. In the relationship between rate and PSNR, it is clear from Haar and Biorthogonal, that the higher the rate, the higher the PSNR. In Daubechies, the decrease in PSNR is not too significant with decreasing rate. In general, test image 1 applies a directly proportional relationship between rate and PSNR. The higher the rate, the higher the PSNR. This is because the lower the rate (image size), the more information is lost, which results in a lower PSNR value. For image 1 it can be seen that Haar and Biorthogonal wavelets produce better PSNR values and rates than Daubechies wavelets for all thresholds used. The same results were also obtained for each subsequent test image. The next test is the compression time test for medical images shown in Figure 5.

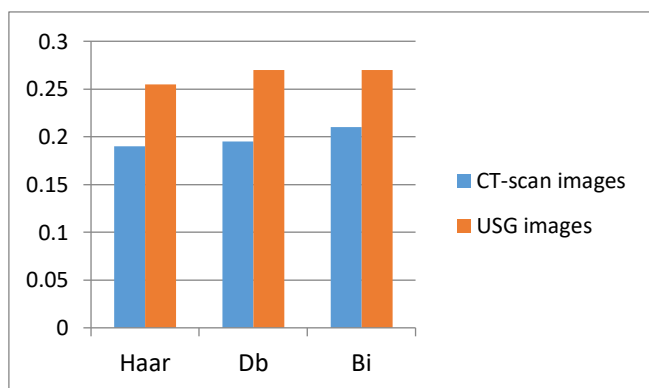


Fig 5. The results of testing the compression time on wavelets

The results of the compression time test on medical images with three wavelets as shown in Figure 5, that the fastest average processing time for CT-scan medical images occurs in Haar wavelets. In general, compression time for all wavelet methods, CT-scan medical images compress the fastest. While the longest time mostly occurs in ultrasound medical images on Biorthogonal wavelets. This happens because all the processes that occur are the same, the only difference is the value of the scale function on the wavelet and the value of the thresholding results which have different lengths.

The third test is the decompression process time. The decompression process is the process of returning the image to its original state so that the image can be recognized normally. The results of testing the decompression process time are shown in table III.

TABLE 3.  
DECOMPRESSION TIME

| decompression   | wavelet | CT-scan images (sc) | USG images (sc) |
|-----------------|---------|---------------------|-----------------|
| decode RLE      | Haar    | <b>0,65</b>         | 0,93            |
|                 | Db      | <b>0,65</b>         | 0,91            |
|                 | Bi      | 0,66                | 0,93            |
| inverse wavelet | Haar    | 0,87                | 1,07            |
|                 | Db      | 0,89                | 1,08            |
|                 | Bi      | 0,89                | 1,06            |

The decompression process in this study observed the RLE decoding and inverse wavelet (IW) decompression time on medical images. The fastest RLE decoding processing time occurs in Haar and Daubechies wavelets for CT-scan images. The RLE decoding time for the three wavelets was actually not significantly different for the two medical images. The fastest IW time occurs in the Haar wavelet for CT-scan images, while the longest occurs in the Daubechies wavelet for USG images, but the time difference between the three is not significantly different. Overall the decompression time for both medical images is the fastest in the Haar wavelet and the longest in the Daubechies wavelet [33].

#### IV. CONCLUSIONS

Compression research on medical images was carried out using the wavelet haar, Daubechies, and biorthogonal methods. The role of RLE coding is very significant because it produces a decomposition with shorter data representation and the compression ratio can be increased without reducing image quality. The test was carried out using three different threshold values, namely 30, 40, and 50. The test results concluded that the larger the threshold, the higher the compression ratio value while the PSNR value will be lower. the best result of the compression ratio is on the Haar wavelet. Likewise in terms of compression and decompression time, the Haar wavelet is the fastest but the time difference is not significantly different. The test results on both medical images show that CT scan images on Haar and biorthogonal wavelets are the best with an average compression ratio of 40.76%, a PSNR of 33.77, and a compression time of 0.19 seconds and an RLE decoding time of 0.65 seconds.

#### ACKNOWLEDGMENT

We would like to thank the Politeknik Negeri Bali Center for Research and Community Service for supporting the grand research as well as the research team from Universiti Sains Malaysia and STMIK STIKOM Indonesia, Denpasar.

#### REFERENCES

- [1] Cinaglia, P., D. Mirarchi, and P. Veltri, "Information Retrieval in Life Sciences", in *Encyclopedia of Bioinformatics and Computational Biology*, S. Ranganathan, et al., Editors. 2019, Academic Press: Oxford. p. 1104-1108.

- [2] Jinguo, W., W. Na, and M. Haichun, "Application of computer technology in medical image processing". in *Proceedings of the 4th International Conference on Information Technology and Management Innovation*. 2015. Atlantis Press.
- [3] Thandapani, S., et al., "IoT with Deep CNN: AI-Based Intelligent Support System for Pandemic Diseases". *Electronics*, 2023. 12(2): p. 424.
- [4] Masarwa, S., O. Kreichman, and S. Gilaie-Dotan, "Larger images are better remembered during naturalistic encoding". *Proceedings of the National Academy of Sciences*, 2022. 119(4): p. e2119614119.
- [5] Xin, G. and P. Fan, "A lossless compression method for multi-component medical images based on big data mining". *Scientific Reports*, 2021. 11(1): p. 12372.
- [6] Kaur, R. and Pooja, "A Review of Image Compression Techniques". *International Journal of Computer Applications*, 2016. 142: p. 8-11.
- [7] Singh, M., et al., "Various Image Compression Techniques: Lossy and Lossless". *International Journal of Computer Applications*, 2016. 142: p. 23-26.
- [8] Pl, C. and A. Tamilmathi, "Effective lossy and lossless color image compression with Multilayer Perceptron". *International Journal of Engineering and Technology(UAE)*, 2018. 7: p. 9-14.
- [9] Lakshmi, N.A., "Lossy Image Compression Techniques". *American Journal of Computer Science and Information Technology*, 2021. 9(7).
- [10] Hu, Y., et al., "Learning End-to-End Lossy Image Compression: A Benchmark". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022. 44(8): p. 4194-4211.
- [11] Ayoobkhan, M.U.A., E. Chikkannan, and K. Ramakrishnan, "Lossy image compression based on prediction error and vector quantisation". *EURASIP Journal on Image and Video Processing*, 2017. 2017(1): p. 35.
- [12] Rahman, M.A. and M. Hamada, "Lossless Image Compression Techniques: A State-of-the-Art Survey". *Symmetry*, 2019. 11, DOI.
- [13] Bull, D.R. and F. Zhang, "Chapter 7 - Lossless compression methods", in *Intelligent Image and Video Compression (Second Edition)*, D.R. Bull and F. Zhang, Editors. 2021, *Academic Press: Oxford*. p. 225-270.
- [14] Lee, S.-W. and H.-Y. Kim, "An energy-efficient low-memory image compression system for multimedia IoT products". *EURASIP Journal on Image and Video Processing*, 2018. 2018(1): p. 87.
- [15] Singh, U. and M. Kumar, "A Review: Compression on Medical Images". *International Journal of Engineering and Technical Research*, 2022. Vol. 11: p. 103-109.
- [16] Rojas-Hernández, R., et al., "Lossless Medical Image Compression by Using Difference Transform". *Entropy (Basel)*, 2022. 24(7): p. 951.
- [17] Prasetyowati, A., N. Suryaningsih, and V.A. Pratomo, "Comparison of Wavelet and Hybrid (ICA and Wavelet) Methods in Separation of Sound Frequency in Forensic Audio Models". in *The 5th International Conference Innovation Research for Science, Technology, and Culture*. 2020. Faculty of Engineering Universitas Pancasila.
- [18] Ramaprakash, C., et al., "Compression of biomedical images using DDWT and noise shaping algorithm". *International Journal of Health Sciences*, 2022. 6(S6): p. 4212-4223.
- [19] Mason, A., et al., "Comparison of Objective Image Quality Metrics to Expert Radiologists' Scoring of Diagnostic Quality of MR Images". *IEEE Trans Med Imaging*, 2019. 39(4): p. 1064-1072.
- [20] Gupta, A., A. Bansal, and V. Khanduja, "Modern Lossless Compression Techniques: Review, Comparison and Analysis" 2017.
- [21] Gupta, A. and S. Nigam, "A Review on Different Types of Lossless Data Compression Techniques". *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 2021.
- [22] Vilimek, D., et al., "Comparative analysis of wavelet transform filtering systems for noise reduction in ultrasound images". *PLOS ONE*, 2022. 17(7): p. e0270745.
- [23] Dumitrescu and C.-A. Boiangiu, "A Study of Image Upsampling and Downsampling Filters". *Computers*, 2019. 8: p. 30.
- [24] Fitriya, L.A., T. Purboyo, and A. Prasasti, "A review of data compression techniques". *International Journal of Applied Engineering Research*, 2017. 12: p. 8956-8963.
- [25] Sahooinst, R., S. Roy, and S.S. Chaudhuri, "Haar Wavelet Transform Image Compression Using Various Run Length Encoding Schemes". 2015. *Cham*: Springer International Publishing.
- [26] Kalavathi, P. and S. Boopathiraja, "A Wavelet Based Image Compression with RLC Encoder". *Computational Methods, Communication Techniques and Informatics*, 2017: p. 289-292.
- [27] Abu-Taieh, E., "The Pillars of Lossless Compression Algorithms a Road Map and Genealogy Tree". *International Journal of Applied Engineering Research*, 2018. 13(6): p. 3296-3414.
- [28] Weisz, F., "The Inverse of the Continuous Wavelet Transform". 2018. *Cham*: Springer International Publishing.
- [29] Ramlie, F., et al., "Classification Performance of Thresholding Methods in the Mahalanobis-Taguchi System". *Applied Sciences*, 2021. 11: p. 3906.
- [30] Mason, A., et al., "Comparison of Objective Image Quality Metrics to Expert Radiologists' Scoring of Diagnostic Quality of MR Images". *IEEE Transactions on Medical Imaging*, 2020. 39(4): p. 1064-1072.
- [31] Gibson, J., "Rate Distortion Functions and Rate Distortion Function Lower Bounds for Real-World Sources". *Entropy*, 2017. 19(11): p. 604.
- [32] Sinhal, R., I. Ansari, and D. Jain, "Real-time watermark reconstruction for the identification of source information based on deep neural network". *Journal of Real-Time Image Processing*, 2020. 17.
- [33] Maghari, A., "A Comparative Study of DCT and DWT Image Compression Techniques combined with Huffman coding". *Jordanian Journal of Computers and Information Technology (JJCIT)*, 2019. 5: p. 73-87.



I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

---

**[JOIV] Editor Decision**

---

**Alde Alanda** <aldealanda@gmail.com>

Tue, Jul 11, 2023 at 9:38 PM

To: I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

I Nyoman Gede Arya Astawa:

We have reached a decision regarding your submission to JOIV : International Journal on Informatics Visualization, "Comparison of the Packet Wavelet Transform Method for Medical Image Compression".

Our decision is: Revisions Required

Alde Alanda  
(Scopus ID: 57203718850); Politeknik Negeri Padang, Sumatera Barat  
Phone 81267775707  
Fax 81267775707  
[aldealanda@gmail.com](mailto:aldealanda@gmail.com)

Alde Alanda

-----  
Reviewer C:

- Describe how your research differs from prior work by analyzing the gaps between it and the work you are currently doing. Describe the novelty you are looking for in this study.
- Correct writing formula 4
- The article's writing could require some work because some punctuation marks are used incorrectly. Additionally, ensure sure the tables and figures are written according to the template. Between tables I, II, and table 3, the writing of the table title numbering is different.
- To separate a number's decimal value, use a period rather than a comma.
- In your article, you are not explained how you measure the compression time of the two types of images so as to produce the values in table 3.
- The conclusion includes a summary of the quantitative and qualitative findings as well as the author's own assessment of the findings and shortcomings of the study for prospects for future research and growth. Refine your conclusion and connect it to your article's title.
- Add references (minimum 40 references) related to the topic and make sure they are referred to in your writing.

-----  

---

<http://joiv.org/index.php/joiv>



I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

## [JOIV] Editor Decision

I Nyoman Gede Arya Astawa <arya\_kmg@pnb.ac.id>  
To: Alde Alanda <aldealanda@gmail.com>

Fri, Jul 14, 2023 at 11:20 AM

dear,  
Alde Alanda  
along with this we send the repair

| improvement comments   | improvement   |
|--|---|
| - Describe how your research differs from prior work by analyzing the gaps between it and the work you are currently doing. Describe the novelty you are looking for in this study.  | The contribution of this study is to recommend a wavelet method, namely Haar, Daubechies, and Biorthogonal for a high compression ratio with good decompressed image quality. The PWT method used in this study is to perform image decomposition at low and high frequencies. This decomposition makes it possible to store all image features and finally, the ratio can be controlled by thresholds and combining them with RLE. |
| - Correct writing formula 4  | Formula 4 has been corrected  |
| - The article's writing could require some work because some punctuation marks are used incorrectly. Additionally, ensure sure the tables and figures are written according to the template. Between tables I, II, and table 3, the writing of the table title numbering is different. | writing the numbering of table titles I, II, and III is in accordance with the template   |
| - To separate a number's decimal value, use a period rather than a comma.  | Separating decimal values already uses a dot  |
| - In your article, you are not explained how you measure the compression time of the two types of images so as to produce the values in table 3.   | The results of measuring compression and decompression times are shown in Tables III, IV, and V   |
| - The conclusion includes a summary of the quantitative and qualitative findings as well as the author's own assessment of the findings and shortcomings of the study for prospects for future research and growth. Refine your conclusion and connect it to your article's title.     | Conclusions have been corrected according to the discussion and test results  |
| - Add references (minimum 40 references) related to the topic and make sure they are referred to in your writing.  | References have been added more than 40 references  |

thank's

salam  
Dr. I Nyoman Gede Arya Astawa, ST., M.Kom  
(Komang Arya)  
Politeknik Negeri Bali  
Jurusan Teknik Elektro  
Prodi Manajemen Informatika  
Telp: 08123814894

[Quoted text hidden]



**1732-3874-1-SM- Revisi1.docx**

2124K

# Comparison of the Packet Wavelet Transform Method for Medical Image Compression

I Made Ari Dwi Suta Atmaja<sup>a\*</sup>, Wilfridus Bambang Triadi<sup>b</sup>, I Nyoman Gede Arya Astawa<sup>c</sup>, Made Leo Radhitya<sup>d</sup>

<sup>a c</sup> Department of Electrical Engineering, Politeknik Negeri Bali, Badung, 80361, Indonesia

<sup>b</sup> School of Computer Sciences, Universiti Sains Malaysia, Malaysia

<sup>d</sup> Department of Informatics, Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali, 80225, Indonesia

\*Corresponding author: arisuta@pnb.ac.id

**Abstract**— Medical images are often used for educational, analytical, and medical diagnostic purposes. Medical image data requires large amounts of storage on computers. Three types of codecs namely Haar, Daubechies, and Biorthogonal were used in this study. This study aims to find the best wavelet method of the three tested wavelet methods (Haar, Daubechies, and Biorthogonal). This study uses medical images that represent USG images and CT-scan images as testing data. The first test is carried out by comparing the threshold ratio. There are three threshold values used, namely 30, 40, and 50. The second test looks for PSNR values with different thresholds. The third test looks for a comparison of the rate (image size) to the PSSR value. The final test is to find the compression time and decompression time for each medical image. The results of the first compression ratio test on both medical images showed that CT scan images on Haar and Biorthogonal wavelets were the best with an average compression ratio of 40.76% and a PSNR of 33.77. For testing with a larger image size, the PSNR obtained is also getting bigger. The average compression time is 0.52 seconds and the decompression time is 2.27 seconds. Based on the test results, this study recommends that the Daubechies wavelet method is very good for compression, which is 0.51 seconds, and the Biorthogonal wavelet method is very good for medical image decompression, which is 1.69 seconds.

**Keywords**— Medical Image; wavelets; Haar; Daubechies; Biorthogonal

*Manuscript received 15 Oct. 2020; revised 29 Jan. 2021; accepted 2 Feb. 2021. Date of publication 17 Feb. 2021. International Journal on Informatics Visualization is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.*



## I. INTRODUCTION

Medical images are often used for learning, analysis, and medical diagnosis [1] so in the field of medical education, medical images play a very important role [2]. According to researchers [3, 4], a medium-sized hospital alone currently produces an average of 5GB to 15GB of data. This will cause difficulties for hospitals to handle such large data, both in storage and in sending image data. Images that have a large capacity require a long time to be sent [5], so the desire to get fast information cannot be accommodated properly. One solution to this problem is image compression [1].

Image compression is a method that aims to reduce memory usage [6, 7], making it easier to store. Processing and transmitting digital data will require a shorter time than

uncompressed data [8]. There are many methods for image compression today. In general, compression methods are divided into two types: lossy and lossless [9, 10]. Lossy compression usually has a good ratio, but the resulting image quality is lower due to missing information from the original image [9, 11-13]. Lossless compression is a compression technique with the quality of the reconstructed image being the same as the original image, but in most natural images it produces a bad ratio [9, 10, 14, 15].

When compressing an image, there are two parameters that must be measured, namely the compression ratio and the decompressed image quality. A good method for compression is one that is capable of producing a high compression ratio, but the resulting reduction in image quality is still tolerated by the human eye [8, 16]. Besides, when the compression method is applied, we cannot let go of the decompression process. A

medical image is an image that will be analyzed and used by doctors, thus the quality of the reconstructed medical image must not decrease and is still acceptable. There are several studies related to medical image compression, such as those carried out by [6, 15, 17, 18]. The number of studies on medical image compression at present shows that this problem is a concern for many researchers in the world. Based on these data, a good compression method is needed. This research concerns medical image compression by applying wavelet packet transform (PWT) and lossless RLE coding to maintain good image quality.

The basic principle of PWT is to obtain a time and scale representation of a signal using digital filter techniques and sub-sampling operations. The wavelet transform uses two important components in the process, namely, scaling (scaling function) or low-pass filtering and wavelet (wavelet function) or high-pass filtering. Several studies such as [19, 20] show that wavelets can provide good image quality with high compression ratios. Wavelet techniques usually use the discrete wavelet transform (DWT), where only low-frequency elements are decomposed deeper, while high-frequency elements are not decomposed any further. This study decomposes each element, both low and high frequency, using wavelet packet transform (PWT). The fundamental difference between DWT and PWT is that PWT does not only decompose low frequency elements but also high-frequency elements. This is also an advantage of PWT compared to DWT [21]. The resulting ratio will be regulated with the provision of a threshold. According to Kharate and Patil [21], a good ratio can be obtained by providing an appropriate threshold.

The Run Length Encoding (RLE) compression technique has been widely used. This method utilizes the repetition of pixel values that occur sequentially. In addition, RLE works well on data that has a large number of data repetitions. RLE is a lossless compression method that will maintain the original quality of data both before and after compression. So, this method will work well when combined with wavelet transformation on medical images. This combination makes no data lost. Research that has been done for image compression with RLE, was carried out by [15, 22, 23] who used Enhanced RLE, by modifying ordinary RLE, which aims to produce a perfect image reconstruction ratio.

The contribution of this study is to recommend a wavelet method, namely Haar, Daubechies, and Biorthogonal for a high compression ratio with good decompressed image quality. The PWT method used in this study is to perform image decomposition at low and high frequencies. This decomposition makes it possible to store all image features and finally, the ratio can be controlled by thresholds and combining them with RLE.

## II. MATERIAL AND METHOD

There are several stages in medical image compression research as shown in Figure 1. The first process is to insert medical images from CT-scan images or USG images. The second process is compression using the Haar, Daubechies, and Biorthogonal wavelet methods, where in this study the decomposition level will be selected by the user. The results of the decomposition in matrix form are given a threshold and data that has a value below the threshold is changed to zero.

The results of this decomposition are encoded using RLE with the hope that the data representation can be shorter so that the compression ratio can be increased without reducing image quality. RLE code that has been built, and stored in a file. The decompression process is done by opening the file that contains the RLE code data. Then read the data to return the data with RLE decoding. RLE decoding produces data that is reconstructed with inverse wavelet (IW). The results of this reconstruction are presented to the user as a decompressed image. In this study, data compression is the process of reducing the number of bits in data, while data decompression is the process of returning compressed data to its original form.

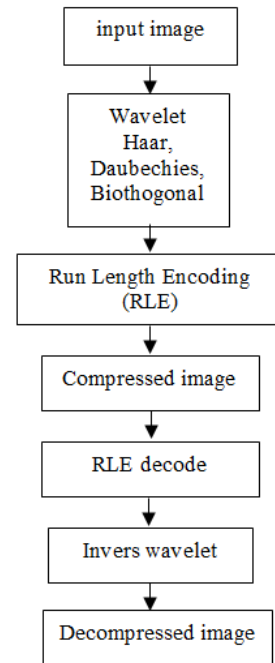


Fig 1. System flow chart

### A. Wavelet

In the wavelet transform, digital filtering techniques are used to get a depiction of a digital signal's time scale[24]. Broadly speaking, the process in this technique is to pass the signal to be analyzed on a filter with different frequencies and scales. Filterization itself is a function used in signal processing. Wavelets can be realized using filter iterations with scaling. The resolution of the signal, which is the average of the amount of detailed information in the signal, is determined through this filtration, and the scale is obtained by upsampling and downsampling[25].

The selection of wavelets in this study is based on several considerations: first, the wavelet transform can be performed perfectly with linear time. Second, practically speaking, the wavelet coefficients are mostly small or zero. This condition is very beneficial, especially in the field of data compression. Finally, wavelets are adaptable to many types of functions, such as discontinuous functions, and functions defined in a bounded domain[26].

The type of wavelet chosen in this study is the type of wavelet that is often used by researchers, namely Haar, Daubechies, and Biorthogonal wavelets.

### B. RLE and RLE Decode

In data compression, there are two types of methods: lossless and lossy compression [22]. Run Length Encoding (RLE) belongs to one of the simplest lossless types of data compression schemes and is based on the simple principle of data encoding [22, 23]. The RLE method is very suitable for compressing data containing repeated characters. The working system using the RLE (Run Length Encoding) method is as follows: (1) RLE works by reducing the physical size by repeating a string of characters/data bits; (2) This looping string is called RUN and is usually encoded in 2 bits. The first bit is the number of repetitions and the second bit is the repeated character [27].

Run Length Encoding (RLE) is done by counting the number of occurrences of a value in a certain sequence. In this method, each value will be written first. If all values have been written, it will be followed by the frequency of occurrence of each value. The process of decoding the results of the RLE is carried out by writing the value of the number of times it appears. The result is an  $m \times n$  matrix based on the data stored in the file being read.

### C. Inverse wavelet

This study uses wavelets as a first step to decompose images at both low and high frequencies. This first step corresponds to the final step of the wavelet inverse. Wavelet decomposes the image by downsampling, and vice versa, the inverse reconstructs the image by upsampling [28]. All wavelet and inverse wavelet steps were carried out in this study. The process of inverse wavelet transformation or often also called the process of reconstruction of the matrix, so that a value is generated for the output image.

### D. Thresholding

Thresholding is a method of image segmentation in which the process is based on differences in the degree of the grayness of the image [29]. In this process, it takes a limit value called the threshold value. The thresholding stage is carried out to reduce data that is considered insignificant, namely data below a certain threshold. All values below the threshold will be set to zero. In this study, to test the compression ratio and image quality, several threshold values were used.

### E. Testing

Medical image quality testing uses the Peak Signal-To-Noise Ratio (PSNR). The PSNR calculation will begin by finding the Mean Square Error (MSE) value with equation 1, then processing it with the PSNR calculation in Equation 2. The PSNR value for lossy compression is 30 to 50 dB [26]. The equation for calculating MSE is as follows:

$$MSE = \frac{1}{MN} \sum_{i=1}^N \sum_{j=1}^M (f_{ij} - f'_{ij})^2 \quad (1)$$

Where  $f_{ij}$  is the original image,  $f'_{ij}$  is the decompressed image,  $M$  and  $N$  are the image dimensions. Meanwhile PSNR is calculated in the following way:

$$PSNR = 20 \times \log_{10} \left( \frac{b}{MSE} \right) \quad (2)$$

The medical images tested were two types of gray medical images, namely CT-scan images and USG images. This study used threshold values of 30, 40, and 50. The test results are recorded in the compression ratio, PSNR, compression time, and decompression time table. The final results shown are in the form of average time, compression ratio and PSNR of all test images. The compression ratio is calculated using equation 3.

$$Ratio = \frac{(original\ image - compressed\ image)}{original\ image} \quad (3)$$

According to [30], image quality is considered low if the PSNR value is less than 30dB and image quality is considered high if the PSNR value is above 40dB. Meanwhile, if the PSNR value is between 30dB and 40dB, then the image quality is still acceptable.

### F. Rate Distortion

Rate distortion is concerned with the representation of the source with the smallest possible bit value for a particular desired quality [31]. Source data for rate-distortion can be images, videos, or text files. Each different source will have its own technique for representing its distortion rate, for example, voice data will be different from video data.

### G. Bit rate

Bit rate is the average bit required to represent a pixel in an image. The equation that shows the bit rate value is shown in Equation 4.

$$Bit\ rate = \frac{J_s}{I_s} \text{ bpps} \quad (4)$$

Where  $J_s$  is the compressed image file size, while  $I_s$  is the number of pixels in an image. The unit of bit rate is bits per pixel (bpps).

## III. RESULT AND DISCUSSION

This study used images from two medical devices, 15 USG images and 15 CT-scan images. Both image files use bitmap format. Medical image testing is carried out by testing the image ratio, image quality, and compression time on three types of wavelets, namely Haar, Daubechies, and Biorthogonal.

Figure 2. Shows the test image used in the study. The test images displayed are only four of the 30 test images. Each test image has a different file capacity. Figures 2a and 2c represent CT-scan test images while Figures 2b and 2d represent USG test images.



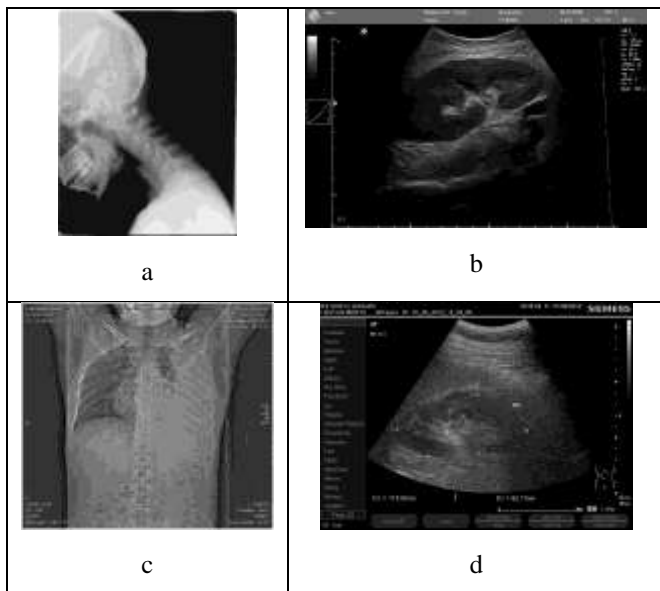


Fig. 2 (a) test image 1, (b) test image 2, (c) test image 3, (d) test image 4

Based on Figure 2, all of these images were processed using the Haar, Daubechies, and Biorthogonal wavelet methods. Image data processing is done by testing each image and the results are recorded in the table. Average test results as shown in the table. The results of the first test, namely testing the compression ratio of two types of medical images on the three types of wavelet method with a threshold of 30, 40, and 50 are shown in Table I.

TABLE I  
RATIO TEST RESULTS

| Wavelet | Threshold | CT-scan images | USG images |
|---------|-----------|----------------|------------|
| Haar    | T30       | 35.69%         | 30.36%     |
|         | T40       | 41.57%         | 39.58%     |
|         | T50       | 45.01%         | 45.56%     |
| Db      | T30       | 22.69%         | 9.21%      |
|         | T40       | 29.59%         | 22.51%     |
|         | T50       | 36.24%         | 31.48%     |
| Bi      | T30       | 35.69%         | 30.36%     |
|         | T40       | 41.57%         | 39.58%     |
|         | T50       | 45.01%         | 45.56%     |

Table I explains that of all compressed image tests it worked well. The increase in the threshold was tested on CT-scan images and ultrasound images. The test results show that the higher the threshold, the higher the compression ratio percentage[32]. This can happen because the larger the threshold, the more information is cut and the value is changed to zero, so that the storage memory can be reduced and the image quality decreases. At all thresholds, the resulting ratio of the Daubechies wavelet is quite low, compared to the ratio produced by the Haar and Biorthogonal wavelets [33]. The best compression ratio is obtained at a threshold of 50. The compressed image test results show that increasing the threshold results in a higher compression ratio[32, 34].

TABLE II  
PSNR TEST RESULTS

| Wavelet | Threshold | CT-scan images | USG images |
|---------|-----------|----------------|------------|
| Haar    | T30       | 34.94          | 33.22      |
|         | T40       | 33.63          | 31.82      |
|         | T50       | 32.74          | 30.69      |
| Db      | T30       | 23.08          | 32.48      |
|         | T40       | 22.97          | 31.12      |
|         | T50       | 22.78          | 30.01      |
| Bi      | T30       | 34.94          | 33.22      |
|         | T40       | 33.63          | 31.82      |
|         | T50       | 32.65          | 30.69      |

The results of the second test are to determine the quality of medical images using the PSNR shown in Table II. The results are different from the first test where the greater the threshold on each wavelet, the lower the PSNR value[35, 36]. This decrease in PSNR occurs in both types of medical images. PSNR values vary from 22 to 35. For Haar and Biorthogonal wavelets, the resulting PSNR is still above 30, while for Daubechies wavelets on USG images, the results are above 30, while on CT-scan images it is below 30 and according to [30] it's still acceptable. The test results on the test images show that the larger the threshold, the lower the PSNR value[34].

The next test is to determine the relationship between image size and the resulting PSNR value. This test produces a graph of the level of distortion rates for each test image. The test results are shown in Figures 3, 4, 5 and 6.

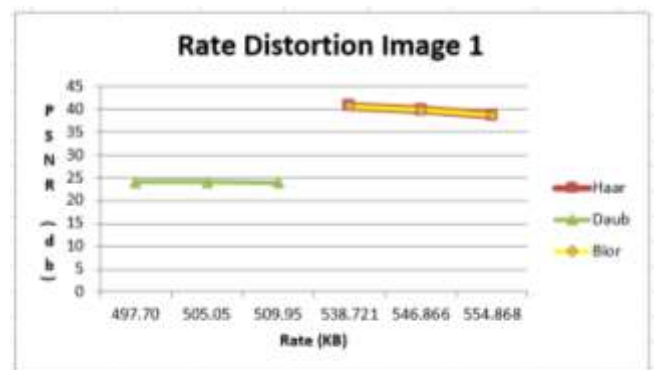


Fig. 3 Rate Distortion in test image 1

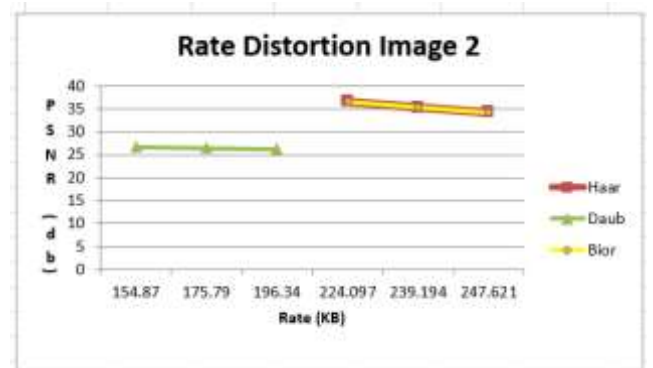


Fig. 4 Rate Distortion in test image 2

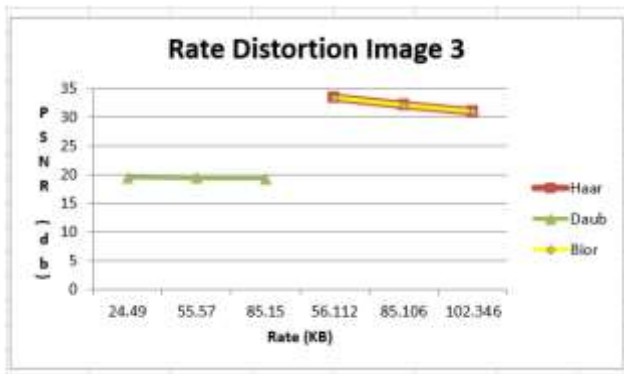


Fig. 5 Rate Distortion in test image 3

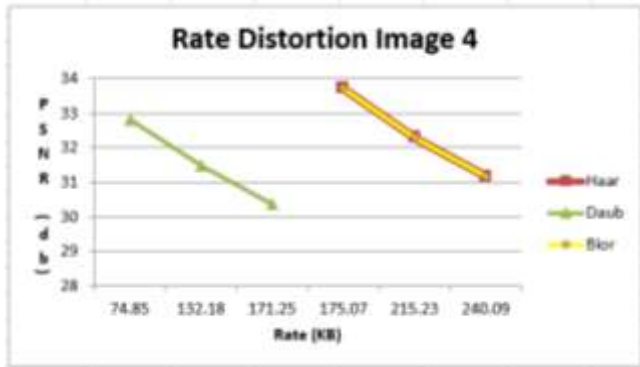


Fig. 6 Rate Distortion in test image 4

Figures 3, 4, 5, and 6 show the distortion rate graphs for test image 1, 2, 3, and 4, where the x-axis shows the rate. The y-axis shows the PSNR. The graph shows that the PSNR value when using the Daubechies wavelet is lower than when using the Haar wavelet and Biorthogonal wavelet. This could be due to the fact that the Haar wavelet and Biorthogonal wavelets are more squares in shape than the Daubechies wavelets which tend to be sharp. This difference causes Haar wavelets to be more capable of producing good-quality filters for two-dimensional objects. Meanwhile, in terms of the resulting rate, the rate generated by Haar and Biorthogonal is lower than that of Daubechies. In the relationship between rate and PSNR, it is clear from Haar and Biorthogonal, that the higher the rate, the higher the PSNR. In Daubechies, the decrease in PSNR is not too significant with decreasing rate. In general, test image 1 applies a directly proportional relationship between rate and PSNR. For image 1 it can be seen that Haar and Biorthogonal wavelets produce better PSNR values and rates than Daubechies wavelets for all thresholds used. The same results were also obtained for each subsequent test image. The test results with different image sizes produce a higher test rate, the higher the PSNR[37]. This is because the lower the rate (image size), the more information is lost, which results in a lower PSNR value[38].

The next test is to determine the compression speed on the CT-scan test images and USG images. The results of this test indicate that there are differences in the results of the compression testing time for the two types of images. More details as in Figure 7.

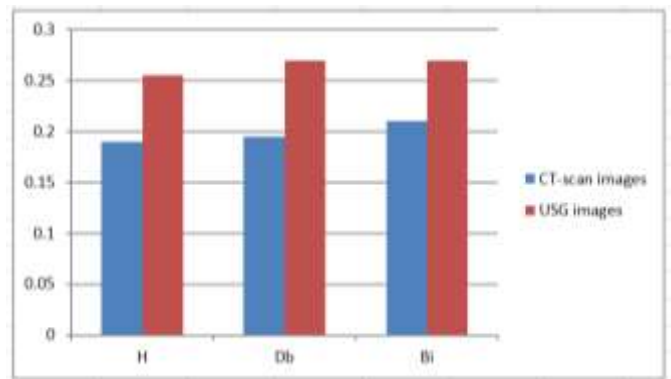


Fig 7. The results of testing the compression time on wavelets

The results of the compression time test on medical images with three wavelets as shown in Figure 7, that the fastest average processing time for CT-scan medical images occurs in Haar wavelets [39]. In general, compression time for all wavelet methods, CT-scan medical images compress the fastest. While the longest time mostly occurs in USG medical images on Biorthogonal wavelets [40]. This happens because all the processes that occur are the same, the only difference is the value of the scale function on the wavelet and the value of the thresholding results which have different lengths. The test results show that the fastest CT-scan image compression time is on Haar wavelets.

The third test is the compression and decompression processing time. The decompression process is the process of returning the image to its original state so that the image can be recognized normally. In this research, a complexity analysis was performed by comparing the compression and decompression times of all codecs. The results of testing the compression and decompression process times are shown in Tables III, IV, and V.

TABLE III  
TIME OF EACH PROCESS WITH HAAR WAVELETS

| Image   | Compression |           |             | Decompression |            |             |
|---------|-------------|-----------|-------------|---------------|------------|-------------|
|         | PWT<br>sc   | RLE<br>sc | Total<br>sc | DRLE<br>sc    | IPWT<br>sc | Total<br>sc |
| Image 1 | 0.81        | 0.27      | 1.08        | 2.88          | 2.39       | 5.27        |
| Image 2 | 0.20        | 0.14      | 0.34        | 0.65          | 0.95       | 1.59        |
| Image 3 | 0.18        | 0.11      | 0.30        | 0.64          | 0.79       | 1.43        |
| Image 4 | 0.25        | 0.15      | 0.40        | 0.92          | 1.03       | 1.95        |

Table III shows the results of the compression and decompression time tests on the four test images with Haar wavelets. The results of this test show that the decompression time is longer than the compression time. The longest time is on the test image 1. The fastest average time for compression and decompression processes using the Haar wavelets method is in USG image.

TABLE IV  
TIME OF EACH PROCESS WITH DAUBECHIES WAVELETS

| Image   | Compression |           |             | Decompression |            |             |
|---------|-------------|-----------|-------------|---------------|------------|-------------|
|         | PWT<br>sc   | RLE<br>sc | Total<br>sc | DRLE<br>sc    | IPWT<br>sc | Total<br>sc |
| Image 1 | 0.73        | 0.28      | 1.01        | 2.95          | 2.25       | 5.20        |
| Image 2 | 0.20        | 0.13      | 0.33        | 0.68          | 0.95       | 1.63        |
| Image 3 | 0.19        | 0.11      | 0.30        | 0.61          | 0.83       | 1.44        |
| Image 4 | 0.27        | 0.14      | 0.41        | 0.93          | 1.02       | 1.95        |

Table IV shows the results of testing the compression and decompression time on the four test images with the Daubechies wavelet. The average compression time is the fastest compared to the decompression time. The results of this test indicate that the average compression time for Daubechies wavelets is the fastest compared to the compression time for Haar and Biorthogonal wavelets, which is 0.512 seconds.

TABLE V  
TIME OF EACH PROCESS WITH BIORTHOGONAL WAVELETS

| Image   | Compression |           |             | Decompression |            |             |
|---------|-------------|-----------|-------------|---------------|------------|-------------|
|         | PWT<br>sc   | RLE<br>sc | Total<br>sc | DRLE<br>sc    | IPWT<br>sc | Total<br>sc |
| Image 1 | 0.77        | 0.27      | 1.04        | 0.66          | 1.01       | 1.67        |
| Image 2 | 0.22        | 0.13      | 0.35        | 0.66          | 1.01       | 1.67        |
| Image 3 | 0.20        | 0.10      | 0.30        | 0.66          | 0.78       | 1.44        |
| Image 4 | 0.27        | 0.14      | 0.41        | 0.94          | 1.07       | 2.01        |

Table V shows the results of the compression and decompression time tests on the four test images with Biorthogonal wavelets. The average decompression time is the fastest compared to the compression time. The results of this test indicate that the fastest decompression time compared to Haar and Daubechies wavelets is 1.69 seconds.

Tables III, IV, and V show the compression and decompression times for all wavelets for Haar wavelets which occurred the fastest, followed by Daubechies. While the longest time mostly occurs in Biorthogonal wavelets. For RLE processing time, Biorthogonal wavelets and Daubechies wavelets are quite fast, while Haar wavelets are one of the slowest. But for each image, the time value is not too different. This happens because all the processes that occur are the same, the only difference is the value of the scale function on these wavelets and the resulting threshold value whose length may be different. Of the two compression steps, the fastest time is found in Haar wavelets, while the longest time is in Biorthogonal wavelets. The fastest RLE decoding processing time occurs in Haar and Daubechies wavelets for CT-scan images. The RLE decoding time for the three wavelets did not differ significantly for the two medical images. The fastest IW time occurs in the Haar wavelet for CT-scan images, while the longest occurs in the Daubechies wavelet for USG images, but the time difference between the three is not significantly different. Overall the decompression time for both medical images is the fastest in the Haar wavelet and the longest in the Daubechies wavelet. The results of testing the compression and decompression times for all test images on the Haar,

Daubechies, and Biorthogonal wavelets methods show that the compression time is faster than the decompression time[41].

#### IV. CONCLUSIONS

Compression research on medical images was carried out using the Haar, Daubechies, and Biorthogonal wavelet methods. The role of RLE encoding is very significant because it produces a decomposition with a shorter data representation and the compression ratio can be increased without reducing image quality. Tests were carried out using three different threshold values, namely 30, 40, and 50. The compressed image test results show that increasing the threshold results in a higher compression ratio and a lower PSNR value. For testing with a larger image size, the PSNR obtained is also getting bigger. Meanwhile, testing the compression and decompression time for all test images using the Haar, Daubechies, and Biorthogonal wavelet methods shows that the compression time is faster than the decompression time. The test results on both medical images showed that the CT-scan images on Haar and Biorthogonal wavelets were the best with an average compression ratio of 40.76%, PSNR 33.77. The average compression time is 0.52 seconds and the decompression time is 2.27 seconds. Based on the test results, this study recommends that the Daubechies wavelet USG is very good for compression, which is 0.51 seconds, and the Biorthogonal wavelet method is very good for medical image decompression, which is 1.69 seconds.

#### ACKNOWLEDGMENT

We would like to thank the Politeknik Negeri Bali Center for Research and Community Service for supporting the grand research as well as the research team from Universiti Sains Malaysia and INSTIKI.

#### REFERENCES

- [1] Cinaglia, P., D. Mirarchi, and P. Veltri, "Information Retrieval in Life Sciences", in *Encyclopedia of Bioinformatics and Computational Biology*, S. Ranganathan, et al., Editors. 2019, Academic Press: Oxford. p. 1104-1108.
- [2] Jinguo, W., W. Na, and M. Haichun, "Application of computer technology in medical image processing". in *Proceedings of the 4th International Conference on Information Technology and Management Innovation*. 2015. Atlantis Press.
- [3] Placidi, G., "Adaptive compression algorithm from projections: application on medical greyscale images". *Computer in Biology and Medicine*, 2009. 39(11): p. 993-999.
- [4] Baeza, I., et al., "ROI-based procedures for progressive transmission of digital images: A comparison". *Mathematical and Computer Modelling*, 2009. 50(5): p. 849-859.
- [5] Masarwa, S., O. Kreichman, and S. Gilaie-Dotan, "Larger images are better remembered during naturalistic encoding". *Proceedings of the National Academy of Sciences*, 2022. 119(4): p. e2119614119.
- [6] Lee, S.-W. and H.-Y. Kim, "An energy-efficient low-memory image compression system for multimedia IoT products". *EURASIP Journal on Image and Video Processing*, 2018. 2018(1): p. 87.
- [7] Parmar, C., "A Review of Image Compression", 2012.
- [8] Kaur, R. and Pooja, "A Review of Image Compression Techniques". *International Journal of Computer Applications*, 2016. 142: p. 8-11.

- [9] Singh, M., et al., "Various Image Compression Techniques: Lossy and Lossless". *International Journal of Computer Applications*, 2016. 142: p. 23-26.
- [10] Pl, C. and A. Tamilmathi, "Effective lossy and lossless color image compression with Multilayer Perceptron". *International Journal of Engineering and Technology(UAE)*, 2018. 7: p. 9-14.
- [11] Lakshmi, N.A., "Lossy Image Compression Techniques". *American Journal of Computer Science and Information Technology*, 2021. 9(7).
- [12] Hu, Y., et al., "Learning End-to-End Lossy Image Compression: A Benchmark". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022. 44(8): p. 4194-4211.
- [13] Ayoobkhan, M.U.A., E. Chikkannan, and K. Ramakrishnan, "Lossy image compression based on prediction error and vector quantisation". *EURASIP Journal on Image and Video Processing*, 2017. 2017(1): p. 35.
- [14] Rahman, M.A. and M. Hamada, "Lossless Image Compression Techniques: A State-of-the-Art Survey". *Symmetry*, 2019. 11, DOI.
- [15] Xin, G. and P. Fan, "A lossless compression method for multi-component medical images based on big data mining". *Scientific Reports*, 2021. 11(1): p. 12372.
- [16] Bull, D.R. and F. Zhang, "Chapter 7 - Lossless compression methods", in *Intelligent Image and Video Compression (Second Edition)*, D.R. Bull and F. Zhang, Editors. 2021, *Academic Press: Oxford*. p. 225-270.
- [17] Singh, U. and M. Kumar, "A Review: Compression on Medical Images". *International Journal of Engineering and Technical Research*, 2022. Vol. 11: p. 103-109.
- [18] Rojas-Hernández, R., et al., "Lossless Medical Image Compression by Using Difference Transform". *Entropy (Basel)*, 2022. 24(7): p. 951.
- [19] Nagaria, B., M.F. Hashmi, and P. Dhakad, "Comparative Analysis of Fast Wavelet Transform for Image Compression for optimal Image Quality and Higher Compression Ratio". *International Journal of Engineering Science and Technology*, 2011. 3.
- [20] Gaber, R., et al., "Image Compression Using High Level Wavelet Transformer with Non-Uniform Quantizer and Different Levels Huffman Codes". *IOP Conference Series: Materials Science and Engineering*, 2020. 765: p. 012072.
- [21] Kharate, G.K. and V.H. Patil, "Color Image Compression Based On Wavelet Packet Best Tree ". *International Journal of Computer Science (IJCS)*, 2010. 7(2): p. 31-35.
- [22] Nagarajan, A. and K. Alagarsamy, "An enhanced approach in run length encoding scheme (EARLE)". *International Journal of Engineering Trends and Technology*, 2011: p. 43-48.
- [23] Sahooinst, R., S. Roy, and S.S. Chaudhuri, "Haar Wavelet Transform Image Compression Using Various Run Length Encoding Schemes". 2015. *Cham: Springer International Publishing*.
- [24] Xizhi, Z., "The Application of Wavelet Transform in Digital Image Processing"2009. 326-329.
- [25] Dumitrescu, D. and C.-A. Boianuiu, "A Study of Image Upsampling and Downsampling Filters". *Computers*, 2019. 8(2): p. 30.
- [26] Urban, K., "257Wavelets on General Domains", in *Wavelet Methods for Elliptic Partial Differential Equations*2008, *Oxford University Press*. p. 0.
- [27] Kalavathi, P. and S. Boopathiraja, "A Wavelet Based Image Compression with RLC Encoder". *Computational Methods, Communication Techniques and Informatics*, 2017: p. 289-292.
- [28] Weisz, F., "The Inverse of the Continuous Wavelet Transform". 2018. *Cham: Springer International Publishing*.
- [29] Rosida Vivin, N., et al., "Image Segmentation of Cows using Thresholding and K-Means Method". *International Journal of Advanced Engineering, Management and Science*, 2017. 3(9).
- [30] Cheddad, A., et al., "Digital image steganography: Survey and analysis of current methods". *Signal Processing*, 2010. 90(3): p. 727-752.
- [31] Gibson, J., "Rate Distortion Functions and Rate Distortion Function Lower Bounds for Real-World Sources". *Entropy*, 2017. 19(11): p. 604.
- [32] Mohindru, P. and Pooja, "Comparative Analysis of Haar, Daubechies and Bior wavelets on Image Compression using Discrete Wavelet Transform". 2022.
- [33] Mishra, V., A. Kumar, and A.K. Jaiswal, "Performance Comparison of Daubechies, Biorthogonal and Haar Transform for Grayscale Image Compression". *International Journal of Computer Applications*, 2015. 126: p. 40-42.
- [34] Singh, S. and S.S. Dwivedi, "Region of Interest Based Lossless and Lossy Compression for Digital Images ". *International Journal of Engineering and Technical Research (IJETR)*, 2018. 8(5): p. 16-21.
- [35] Ayu Jati, P., et al., "Planar scintigraphy image de-noising using coiflet wavelet". *Jurnal Iptek Nuklir Ganendra*, 2021. 24(2): p. 75-83.
- [36] Shaik, A. and V. Thanikaiselvan, "Comparative analysis of integer wavelet transforms in reversible data hiding using threshold based histogram modification". *Journal of King Saud University - Computer and Information Sciences*, 2021. 33(7): p. 878-889.
- [37] Darwis, D., N. Pamungkas, and W. Wamiliana, "Comparison of Least Significant Bit, Pixel Value Differencing, and Modulus Function on Steganography to Measure Image Quality, Storage Capacity, and Robustness". *Journal of Physics: Conference Series*, 2021. 1751: p. 012039.
- [38] G Nath, A., M. S. Nair, and J. Rajan, "Single Image Super Resolution from Compressive Samples Using Two Level Sparsity Based Reconstruction". *Procedia Computer Science*, 2015. 46: p. 1643-1652.
- [39] Zanaty, E. and S. Ibrahim, "High Efficient Haar Wavelets for Medical Image Compression", 2020. p. 547-557.
- [40] Tackie Ammah, P.N. and E. Owusu, "Robust medical image compression based on wavelet transform and vector quantization". *Informatics in Medicine Unlocked*, 2019. 15: p. 100183.
- [41] Bruylants, T., A. Munteanu, and P. Schelkens, "Wavelet based volumetric medical image compression". *Signal Processing: Image Communication*, 2015. 31: p. 112-133.



I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

---

## [JOIV] Editor Decision

---

**Alde Alanda** <aldealanda@gmail.com>

Mon, Jul 31, 2023 at 10:41 PM

To: I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

I Nyoman Gede Arya Astawa:

We have reached a decision regarding your submission to JOIV : International Journal on Informatics Visualization, "Comparison of the Packet Wavelet Transform Method for Medical Image Compression".

Our decision is to: Accept Submission

Starting July 2023. publication fees shall be implemented to all accepted papers. For more details, please email to joiv [at] [pnp.ac.id](mailto:pnp.ac.id). This journal charges the

following author fees (Article Publication Fee):

- Indonesian authors: 4.500.000 IDR per article (Regular)
- Indonesian authors: 6.500.000 IDR per article (Fast Track)
  
- International authors: 380 USD per article (Regular)
- International authors: 480 USD per article (Fast track)

This fee includes:

- DOI registration for each paper
- Checking the article similarity by turnitin
- English proofreading

Alde Alanda  
(Scopus ID: 57203718850); Politeknik Negeri Padang, Sumatera Barat  
Phone 81267775707  
Fax 81267775707  
[aldealanda@gmail.com](mailto:aldealanda@gmail.com)  
Alde Alanda

---

<http://joiv.org/index.php/joiv>



I Nyoman Gede Arya Astawa &lt;arya\_kmg@pnb.ac.id&gt;

---

## author fee

---

I Nyoman Gede Arya Astawa <arya\_kmg@pnb.ac.id>  
To: joiv@pnp.ac.id

Wed, Aug 2, 2023 at 9:47 AM

dear, Alde

we send proof of journal payment

JOIV : International

Journal on Informatics Visualization, "Comparison of the Packet Wavelet Transform Method for Medical Image Compression".

tahnk's

Prof. Dr. I Nyoman Gede Arya Astawa, ST., M.Kom  
(Komang Arya)



Politeknik Negeri Bali

Jurusan Teknik Elektro

Prodi Manajemen Informatika

Telp: 08123814894

---

  
  
**Transaksi Berhasil**


|                   |                                      |
|-------------------|--------------------------------------|
| Rekening Tujuan   | 20520040                             |
| Nama Pemindah     | Bah. ALDE ALAALDA                    |
| Tanggal Transaksi | 01/08/2023                           |
| Waktu Transaksi   | 21:02:39 WIB                         |
| Salah Pemindah    |                                      |
| Bank Tujuan       | BNP                                  |
| Nama Pengirim     | I NYOMAN GEDE ARYA ASTAWA<br>ATRIKSA |
| Nominal           | 4.000.000                            |
| Fee               | 0                                    |
| <b>Total</b>      | <b>4.000.000</b>                     |
| Keterangan        | PUBLIKASI PAK JOIV                   |

**bukti bayar joiv.jpg**  
72K

Home > Archives > Vol 7, No 4 (2023)

## Vol 7, No 4 (2023)

This issue has been available online since **31th December 2023** for the regular issue of December 2023. All articles in this issue (54 original research articles) were authored/co-authored by **195 authors** from **6 countries** (Indonesia, India, Iraq, Malaysia, USA, and United Kingdom).



**Issue Coverage**  
(195 Authors)

**Total 6 Author's Countries**

|                |       |
|----------------|-------|
| United Kingdom | (1)   |
| Indonesia      | (158) |
| India          | (5)   |
| Iraq           | (3)   |
| Malaysia       | (28)  |
| United States  | (1)   |

www.jovv.org

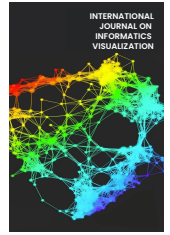
### Table of Contents

#### Articles

|   |                  |
|---|------------------|
| Prediction of Cross-Platform and Native Apps Technology Opportunities for Beginner Developers Using C 4.3 and Naïve Bayes Algorithms            | PDF<br>2145-2153 |
| <p>DOI: 10.30630/jovv.7.4.1514</p> <p>Wawan Gunawan, Ruychal Abubakar Wiyadiputra, Arggi Puspa Sari, Desky Prayana, Eran Rikardo Mingsriwin</p> |                  |

Home > Archives > Vol 7, No 4 (2023)

|  |                  |
|--|------------------|
| Comparison of the Packet Wavelet Transform Method for Medical Image Compression  | PDF<br>2373-2379 |
| <p>DOI: 10.30630/jovv.7.4.1732</p> <p>Made Ari Dwi Satriya, WYTrula Bambang Triada, Nyoman Gede Arya Astawa, Made Leo Rasthyra</p>   |                  |
| A Layered Architecture and Taxonomy for Blockchain-empowered Reputation-based Reward Systems   | PDF<br>2380-2386 |
| <p>DOI: 10.30630/jovv.7.4.1692</p> <p>Jitenendra Singh Yadav, Navendra Singh Yadav, Akhlesh Kumar Sharma</p>                         |                  |
| The Analysis of Organizational Change using Structural Equation Modelling with Mediating Readiness to Change in Higher Education     | PDF<br>2387-2393 |
| <p>DOI: 10.30630/jovv.7.4.2252</p> <p>Rindang Ayu, Nurul-Aziz-Abdullah, Wati Shalviana Wati Sulman, Akhsh Nasir Bin Selamat</p>      |                  |
| Comparison of Parametric and Nonparametric Forecasting Methods for Daily COVID-19 Cases in Malaysia                                  | PDF<br>2394-2403 |
| <p>DOI: 10.30630/jovv.7.4.1819</p> <p>Made Artha Apriyasa, Arsy Amududin</p>   |                  |
| The Extension of the UTAUT2 Model: A Case Study of Indonesian SMEs Acceptance of Social Commerce                                     | PDF<br>2404-2414 |
| <p>DOI: 10.30630/jovv.7.4.1847</p> <p>Arzika Arina, Zuhayra Zuhayra, An Erwan, Ruyha Ma Purabaya, Engku Fadel Hana Syed Zuhairah</p> |                  |



## Comparison of the Packet Wavelet Transform Method for Medical Image Compression

I Made Ari Dwi Suta Atmaja<sup>a,\*</sup>, Wilfridus Bambang Triadi<sup>b</sup>, I Nyoman Gede Arya Astawa<sup>a</sup>,  
Made Leo Radhitya<sup>c</sup>

<sup>a</sup> Department of Electrical Engineering, Politeknik Negeri Bali, South Kuta, Badung, 80361, Indonesia

<sup>b</sup> School of Computer Sciences, Universiti Sains Malaysia, Penang, 11700, Malaysia

<sup>c</sup> Department of Informatics, Institut Bisnis dan Teknologi Indonesia, South Denpasar, Denpasar, 80225, Indonesia

Corresponding author: \*[arisuta@pnb.ac.id](mailto:arisuta@pnb.ac.id)

**Abstract**—Medical images are often used for educational, analytical, and medical diagnostic purposes. Medical image data requires large amounts of storage on computers. Three types of codecs, namely Haar, Daubechies, and Biorthogonal, were used in this study. This study aims to find the best wavelet method of the three tested wavelet methods (Haar, Daubechies, and Biorthogonal). This study uses medical images representing USG and CT-scan images as testing data. The first test is carried out by comparing the threshold ratio. Three threshold values are used, namely 30, 40, and 50. The second test looks for PSNR values with different thresholds. The third test looks for a comparison of the rate (image size) to the PSSR value. The final test is to find each medical image's compression and decompression times. The first compression ratio test results on both medical images showed that CT scan images on Haar and Biorthogonal wavelets were the best, with an average compression ratio of 40.76% and a PSNR of 33.77. The PSNR obtained is also getting more significant for testing with a larger image size. The average compression time is 0.52 seconds, and the decompression time is 2.27 seconds. Based on the test results, this study recommends that the Daubechies wavelet method is very good for compression, which is 0.51 seconds, and the Biorthogonal wavelet method is very good for medical image decompression, which is 1.69 seconds.

**Keywords**—Medical image; wavelets; Haar; Daubechies; Biorthogonal.

Manuscript received 2 Apr. 2023; revised 10 May. 2023; accepted 31 Jul. 2023. Date of publication 31 Dec. 2023.  
International Journal on Informatics Visualization is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.



### I. INTRODUCTION

Medical images are often used for learning, analysis, and medical diagnosis [1], so in medical education, medical images play a vital role [2]. According to researchers [3] and [4], a medium-sized hospital alone currently produces an average of 5GB to 15GB of data. This will cause hospitals difficulty handling such large amounts of data in storage and sending image data. Images with a large capacity require a long time to be sent [5], so the desire to get fast information cannot be accommodated properly. One solution to this problem is image compression [1].

Image compression is a method that aims to reduce memory usage [6], [7], making it easier to store. Processing and transmitting digital data will require a shorter time than uncompressed data [8]. There are many methods for image compression today. In general, compression methods are divided into two types: lossy and lossless [9], [10]. Lossy compression usually has a good ratio, but the resulting image

quality is lower due to missing information from the original image [9], [11]-[13]. Lossless compression is a technique with the reconstructed image's quality being the same as the original image, but in most natural images it produces a bad ratio [9], [10], [14], [15].

When compressing an image, two parameters must be measured: the compression ratio and the decompressed image quality. A good compression method is capable of producing a high compression ratio, but the resulting reduction in image quality is still tolerated by the human eye [8], [16]. Besides, we cannot let go of the decompression process when the compression method is applied. A medical image is an image that will be analyzed and used by doctors; thus, the quality of the reconstructed medical image must not decrease and must still be acceptable. There are several studies related to medical image compression, such as those carried out by [6], [15], [17], [18]. The number of studies on medical image compression shows that this problem is a concern for many researchers worldwide. Based on these data, a good compression method



is needed. This research concerns medical image compression by applying wavelet packet transform (PWT) and lossless RLE coding to maintain good image quality.

The basic principle of PWT is to obtain a time and scale representation of a signal using digital filter techniques and sub-sampling operations. The wavelet transform uses two important components in the process: scaling (scaling function) or low-pass filtering and wavelet (wavelet function) or high-pass filtering. Several studies, such as [19], and [20] show that wavelets can provide good image quality with high compression ratios. Wavelet techniques usually use the discrete wavelet transform (DWT), where only low-frequency elements are decomposed deeper, while high-frequency elements are not further decomposed. This study decomposes each low and high-frequency element using wavelet packet transform (PWT). The fundamental difference between DWT and PWT is that PWT does not only decompose low-frequency elements but also high-frequency elements. This is also an advantage of PWT compared to DWT [21]. The resulting ratio will be regulated with the provision of a threshold. According to Kharate and Patil [21], a good ratio can be obtained by providing an appropriate threshold.

The Run Length Encoding (RLE) compression technique has been widely used. This method utilizes the repetition of pixel values that occur sequentially. In addition, RLE works well on data that has a large number of data repetitions. RLE is a lossless compression method that will maintain the original quality of data both before and after compression. So, this method will work well when combined with wavelet transformation on medical images. This combination makes no data lost. Research that has been done for image compression with RLE, was carried out by [15], [22], [23], who used Enhanced RLE, by modifying ordinary RLE, which aims to produce a perfect image reconstruction ratio.

The contribution of this study is to recommend a wavelet method, namely Haar, Daubechies, and Biorthogonal, for a high compression ratio with good, decompressed image quality. The PWT method used in this study is to perform image decomposition at low and high frequencies. This decomposition makes it possible to store all image features, and finally, the ratio can be controlled by thresholds and combining them with RLE.

## II. MATERIAL AND METHOD

There are several stages in medical image compression research, as shown in Figure 1. The first process is to insert medical images from CT-scan images or USG images. The second process is compression using the Haar, Daubechies, and Biorthogonal wavelet methods, where the decomposition level will be selected by the user in this study. The results of the decomposition in matrix form are given a threshold, and data that has a value below the threshold is changed to zero. The results of this decomposition are encoded using RLE with the hope that the data representation can be shorter so that the compression ratio can be increased without reducing image quality. RLE code that has been built and stored in a file. The decompression process is done by opening the file that contains the RLE code data. Then, read the data to return it with RLE decoding. RLE decoding produces data that is reconstructed with inverse wavelet (IW). The results of this reconstruction are presented to the user as a decompressed

image. In this study, data compression is the process of reducing the number of bits in data, while data decompression is the process of returning compressed data to its original form.

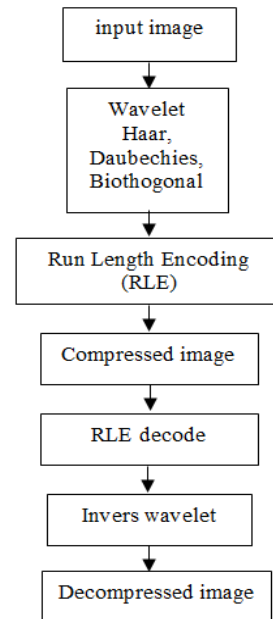


Fig. 1 System flow chart

### A. Wavelet

In the wavelet transform, digital filtering techniques are used to get a depiction of a digital signal's time scale [24]. Broadly speaking, the process in this technique is to pass the signal to be analyzed on a filter with different frequencies and scales. Filterization itself is a function used in signal processing. Wavelets can be realized using filter iterations with scaling. The resolution of the signal, which is the average of the amount of detailed information in the signal, is determined through this filtration, and the scale is obtained by upsampling and downsampling [25].

The selection of wavelets in this study is based on several considerations: first, the wavelet transform can be performed perfectly with linear time. Second, practically speaking, the wavelet coefficients are mostly small or zero. This condition is very beneficial, especially in the field of data compression. Finally, wavelets are adaptable to many functions, such as discontinuous functions and functions defined in a bounded domain [26]. The type of wavelet chosen in this study is the type that is often used by researchers, namely Haar, Daubechies, and Biorthogonal wavelets.

### B. RLE and RLE Decode

Data compression has two types of methods: lossless and lossy compression [22]. Run Length Encoding (RLE) belongs to one of the simplest lossless types of data compression schemes and is based on the simple principle of data encoding [22, 23]. The RLE method is very suitable for compressing data containing repeated characters. The working system using the RLE (Run Length Encoding) method is as follows: (1) RLE works by reducing the physical size by repeating a string of characters/data bits; (2) This looping string is called RUN and is usually encoded in 2 bits. The first bit is the number of repetitions and the second bit is the repeated character [27].

Run Length Encoding (RLE) is done by counting the number of occurrences of a value in a certain sequence. In this method, each value will be written first. If all values have been written, it will be followed by the frequency of occurrence of each value. The process of decoding the results of the RLE is carried out by writing the value of the number of times it appears. The result is an  $m \times n$  matrix based on the data stored in the file being read.

### C. Inverse wavelet

This study uses wavelets as a first step to decompose images at both low and high frequencies. This first step corresponds to the final step of the wavelet inverse. Wavelet decomposes the image by downsampling, and vice versa. The inverse reconstructs the image by upsampling [28]. All wavelet and inverse wavelet steps were carried out in this study. The process of inverse wavelet transformation is often also called the process of reconstruction of the matrix so that a value is generated for the output image.

### D. Thresholding

Thresholding is a method of image segmentation in which the process is based on differences in the degree of the grayness of the image [29]. In this process, it takes a limit value called the threshold value. The thresholding stage is carried out to reduce data considered insignificant, namely data below a certain threshold. All values below the threshold will be set to zero. In this study, several threshold values were used to test the compression ratio and image quality.

### E. Testing

Medical image quality testing uses the Peak Signal-To-Noise Ratio (PSNR). The PSNR calculation will begin by finding the Mean Square Error (MSE) value in Equation (1), and then processing it with the PSNR calculation in Equation 2. The PSNR value for lossy compression is 30 to 50 dB [26]. The Equation for calculating MSE is as follows:

$$MSE = \frac{1}{MN} \sum_{i=1}^N \sum_{j=1}^M (f_{ij} - f'_{ij})^2 \quad (1)$$

Where  $f_{ij}$  is the original image,  $f'_{ij}$  is the decompressed image,  $M$  and  $N$  are the image dimensions. Meanwhile, PSNR is calculated in the following way:

$$PSNR = 20 \times \log_{10} \left( \frac{b}{MSE} \right) \quad (2)$$

The medical images tested were two types of gray medical images: CT-scan and USG. This study used threshold values of 30, 40, and 50. The test results are recorded in the compression ratio, PSNR, compression time, and decompression time table. The final results shown are in the form of average time, compression ratio, and PSNR of all test images. The compression ratio is calculated using Equation 3.

$$Ratio = \frac{(original\ image - compressed\ image)}{original\ image} \quad (3)$$

According to [30], image quality is considered low if the PSNR value is less than 30dB, and image quality is considered high if the PSNR value is above 40 dB. Meanwhile, if the PSNR value is between 30dB and 40dB, then the image quality is still acceptable.

### F. Rate-Distortion

Rate distortion is concerned with the representation of the source with the smallest possible bit value for a particular desired quality[31]. Source data for rate distortion can be images, videos, or text files. Each different source will have its technique for representing its distortion rate. For example, voice data will be different from video data.

### G. Bit rate

Bit rate is the average bit required to represent a pixel in an image. The Equation that shows the bit rate value is shown in Equation 4.

$$Bit\ rate = \frac{J_s}{I_s} \text{ bpp} \quad (4)$$

$J_s$  is the compressed image file size and  $I_s$  is the number of pixels in an image. The unit of bit rate is bits per pixel (*bpp*).

## III. RESULT AND DISCUSSION

This study used images from two medical devices, 15 USG images and 15 CT-scan images. Both image files use bitmap format. Medical image testing is carried out by testing the image ratio, image quality, and compression time on three types of wavelets, namely Haar, Daubechies, and Biorthogonal. Figure 2 shows the test image used in the study. The test images displayed are only four of the 30 test images. Each test image has a different file capacity. Figures 2a and 2c represent CT-scan test images, while 2b and 2d represent USG test images.

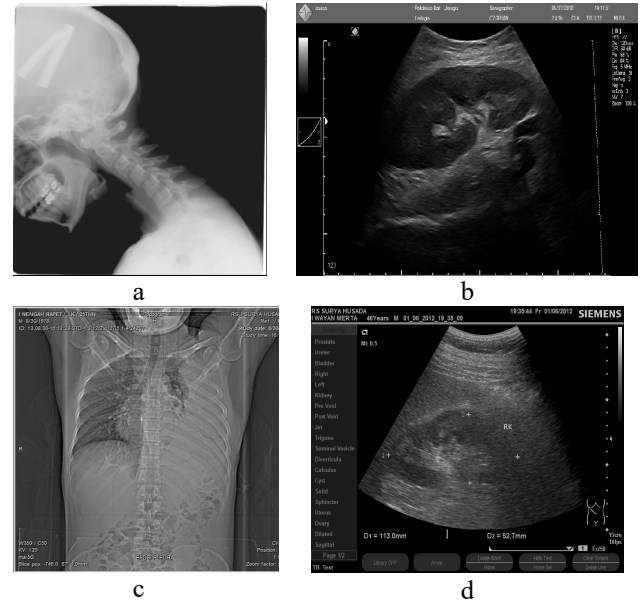


Fig. 2 (a) test image 1, (b) test image 2, (c) test image 3, (d) test image 4

Based on Figure 2, all of these images were processed using the Haar, Daubechies, and Biorthogonal wavelet methods. Image data processing is done by testing each image and the results are recorded in the table. Average test results as shown in the table. The results of the first test, namely testing the compression ratio of two types of medical images on the three types of wavelet method with a threshold of 30, 40, and 50 are shown in Table I.

TABLE I  
RATIO TEST RESULTS

| Wavelet | Threshold | CT-scan images | USG images |
|---------|-----------|----------------|------------|
| Haar    | T30       | 35.69%         | 30.36%     |
|         | T40       | 41.57%         | 39.58%     |
|         | T50       | 45.01%         | 45.56%     |
| Db      | T30       | 22.69%         | 9.21%      |
|         | T40       | 29.59%         | 22.51%     |
|         | T50       | 36.24%         | 31.48%     |
| Bi      | T30       | 35.69%         | 30.36%     |
|         | T40       | 41.57%         | 39.58%     |
|         | T50       | 45.01%         | 45.56%     |

Table I explains that of all compressed image tests, it worked well. The increase in the threshold was tested on CT-scan images and ultrasound images. The test results show that the higher the threshold, the higher the compression ratio percentage [32]. This can happen because the larger the threshold, the more information is cut, and the value is changed to zero so that the storage memory can be reduced and the image quality decreases. At all thresholds, the resulting ratio of the Daubechies wavelet is quite low compared to the ratio produced by the Haar and Biorthogonal wavelets [33]. The best compression ratio is obtained at a threshold of 50. The compressed image test results show that increasing the threshold results in a higher compression ratio[32, 34].

TABLE II  
PSNR TEST RESULTS

| Wavelet | Threshold | CT-scan images | USG images |
|---------|-----------|----------------|------------|
| Haar    | T30       | 34.94          | 33.22      |
|         | T40       | 33.63          | 31.82      |
|         | T50       | 32.74          | 30.69      |
| Db      | T30       | 23.08          | 32.48      |
|         | T40       | 22.97          | 31.12      |
|         | T50       | 22.78          | 30.01      |
| Bi      | T30       | 34.94          | 33.22      |
|         | T40       | 33.63          | 31.82      |
|         | T50       | 32.65          | 30.69      |

The results of the second test are to determine the quality of medical images using the PSNR shown in Table II. The results differ from the first test, where the greater the threshold on each wavelet, the lower the PSNR value[35, 36]. This decrease in PSNR occurs in both types of medical images. PSNR values vary from 22 to 35. For Haar and Biorthogonal wavelets, the resulting PSNR is still above 30, while for Daubechies wavelets on USG images, the results are above 30, while on CT-scan images, it is below 30, and according to [30], it's still acceptable. The test results on the test images show that the larger the threshold, the lower the PSNR value[34].

The next test is to determine the relationship between image size and the resulting PSNR value. This test produces

a graph of the level of distortion rates for each test image. The test results are shown in Figures 3, 4, 5, and 6.

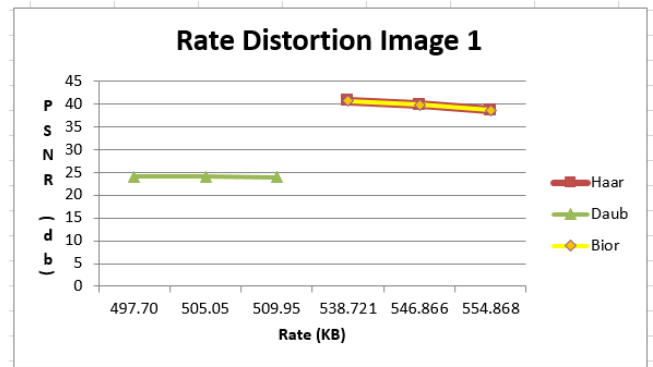


Fig. 3 Rate Distortion in test image 1

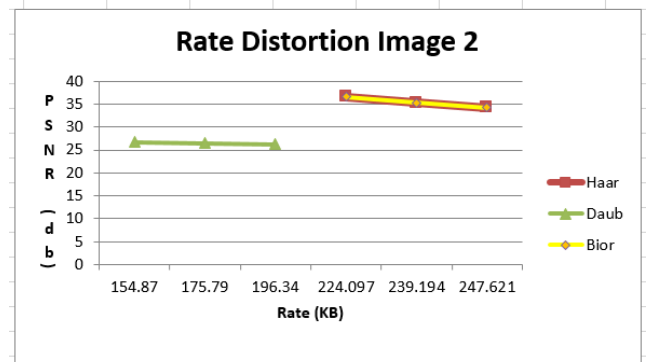


Fig. 4 Rate Distortion in test image 2

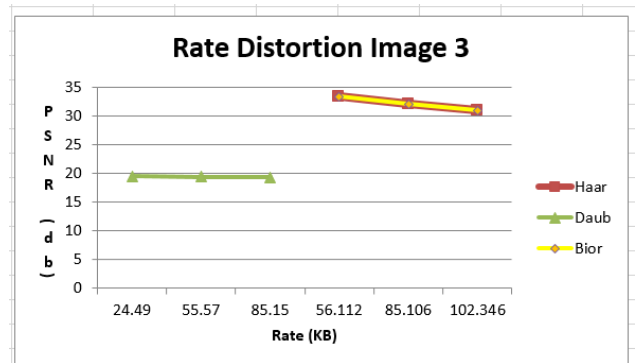


Fig. 5 Rate Distortion in test image 3

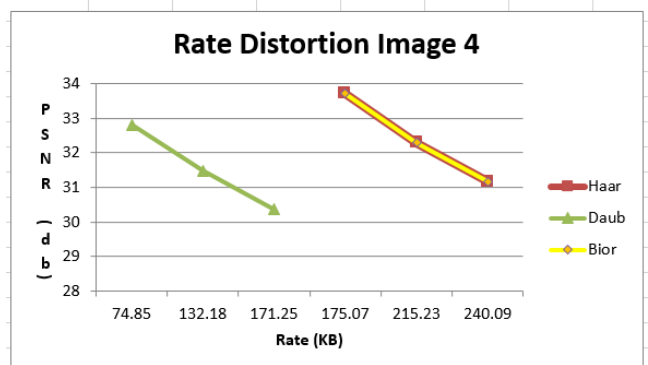


Fig. 6 Rate Distortion in test image 4

Figures 3, 4, 5, and 6 show the distortion rate graphs for test images 1, 2, 3, and 4, where the x-axis shows the rate. The

y-axis shows the PSNR. The graph shows that the PSNR value when using the Daubechies wavelet is lower than when using the Haar wavelet and Biorthogonal wavelet. This could be because the Haar wavelet and Biorthogonal wavelets are more squares in shape than the Daubechies wavelets, which tend to be sharp. This difference causes Haar wavelets to be more capable of producing good-quality filters for two-dimensional objects.

Meanwhile, regarding the resulting rate, the rate generated by Haar and Biorthogonal is lower than that of Daubechies. In the relationship between rate and PSNR, it is clear from Haar and Biorthogonal that the higher the rate, the higher the PSNR. In Daubechies, the decrease in PSNR is not too significant with a decreasing rate. In general, test image 1 applies a directly proportional relationship between rate and PSNR. For image 1, Haar and Biorthogonal wavelets produce better PSNR values and rates than Daubechies wavelets for all thresholds used. The same results were also obtained for each subsequent test image. The test results with different image sizes produce a higher test rate and a higher PSNR[37]. This is because the lower the rate (image size), the more information is lost, which results in a lower PSNR value[38].

The next test is to determine the compression speed on the CT-scan test images and USG images. The results of this test indicate that there are differences in the results of the compression testing time for the two types of images. More details are in Figure 7.

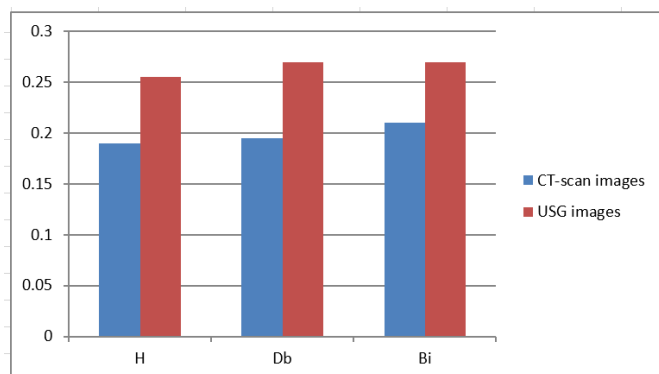


Fig. 7 The results of testing the compression time on wavelets.

The results of the compression time test on medical images with three wavelets as shown in Figure 7, that the fastest average processing time for CT-scan medical images occurs in Haar wavelets [39]. In general, compression time for all wavelet methods, CT-scan medical images compress the fastest. The longest time mostly occurs in USG medical images on biorthogonal wavelets [40]. This happens because all the processes that occur are the same. The only difference is the value of the scale function on the wavelet and the value of the thresholding results which have different lengths. The test results show that the fastest CT-scan image compression time is on Haar wavelets.

The third test is the compression and decompression processing time. The decompression process returns the image to its original state so that it can typically be recognized. This research performed a complex analysis by comparing all codecs' compression and decompression times. Tables III, IV, and V show the results of testing the compression and decompression process times.

TABLE III  
TIME OF EACH PROCESS WITH HAAR WAVELETS

| Image   | Compression |        |          | Decompression |         |          |
|---------|-------------|--------|----------|---------------|---------|----------|
|         | PWT sc      | RLE sc | Total sc | DRLE sc       | IPWT sc | Total sc |
| Image 1 | 0.81        | 0.27   | 1.08     | 2.88          | 2.39    | 5.27     |
| Image 2 | 0.20        | 0.14   | 0.34     | 0.65          | 0.95    | 1.59     |
| Image 3 | 0.18        | 0.11   | 0.30     | 0.64          | 0.79    | 1.43     |
| Image 4 | 0.25        | 0.15   | 0.40     | 0.92          | 1.03    | 1.95     |

Table III shows the results of the compression and decompression time tests on the four test images with Haar wavelets. The results of this test show that the decompression time is longer than the compression time. The longest time is on test image 1. The fastest average time for compression and decompression processes using the Haar wavelets method is in USG image.

TABLE IV  
TIME OF EACH PROCESS WITH DAUBECHIES WAVELETS

| Image   | Compression |        |          | Decompression |         |          |
|---------|-------------|--------|----------|---------------|---------|----------|
|         | PWT sc      | RLE sc | Total sc | DRLE sc       | IPWT sc | Total sc |
| Image 1 | 0.73        | 0.28   | 1.01     | 2.95          | 2.25    | 5.20     |
| Image 2 | 0.20        | 0.13   | 0.33     | 0.68          | 0.95    | 1.63     |
| Image 3 | 0.19        | 0.11   | 0.30     | 0.61          | 0.83    | 1.44     |
| Image 4 | 0.27        | 0.14   | 0.41     | 0.93          | 1.02    | 1.95     |

Table IV shows the results of testing the compression and decompression time on the four test images with the Daubechies wavelet. The average compression time is the fastest compared to the decompression time. The results of this test indicate that the average compression time for Daubechies wavelets is the fastest compared to the compression time for Haar and Biorthogonal wavelets, which is 0.512 seconds.

TABLE V  
TIME OF EACH PROCESS WITH BIORTHOGONAL WAVELETS

| Image   | Compression |        |          | Decompression |         |          |
|---------|-------------|--------|----------|---------------|---------|----------|
|         | PWT sc      | RLE sc | Total sc | DRLE sc       | IPWT sc | Total sc |
| Image 1 | 0.77        | 0.27   | 1.04     | 0.66          | 1.01    | 1.67     |
| Image 2 | 0.22        | 0.13   | 0.35     | 0.66          | 1.01    | 1.67     |
| Image 3 | 0.20        | 0.10   | 0.30     | 0.66          | 0.78    | 1.44     |
| Image 4 | 0.27        | 0.14   | 0.41     | 0.94          | 1.07    | 2.01     |

Table V shows the results of the compression and decompression time tests on the four test images with Biorthogonal wavelets. The average decompression time is the fastest compared to compression time. The results of this test indicate that the fastest decompression time compared to Haar and Daubechies wavelets is 1.69 seconds. Tables III, IV, and V show the compression and decompression times for all wavelets for Haar wavelets, which occurred the fastest, followed by Daubechies. The longest time mostly occurs in biorthogonal wavelets. Biorthogonal wavelets and Daubechies wavelets are quite fast for RLE processing time, while Haar wavelets are one of the slowest. However, for each image, the time value is not too different. This happens

because all the processes that occur are the same. The only difference is the value of the scale function on these wavelets and the resulting threshold value, whose length may differ. Of the two compression steps, the fastest time is found in Haar wavelets, while the longest time is in Biorthogonal wavelets. The fastest RLE decoding processing time occurs in Haar and Daubechies wavelets for CT-scan images. The RLE decoding time for the three wavelets did not differ significantly for the two medical images. The fastest IW time occurs in the Haar wavelet for CT-scan images, while the longest occurs in the Daubechies wavelet for USG images, but the time difference between the three is not significantly different.

Overall, the decompression time for both medical images is the fastest in the Haar wavelet and the longest in the Daubechies wavelet. The results of testing the compression and decompression times for all test images on the Haar, Daubechies, and Biorthogonal wavelets methods show that the compression time is faster than the decompression time [41].

#### IV. CONCLUSIONS

Compression research on medical images was carried out using the Haar, Daubechies, and Biorthogonal wavelet methods. The role of RLE encoding is very significant because it produces a decomposition with a shorter data representation, and the compression ratio can be increased without reducing image quality. Tests were carried out using three different threshold values, namely 30, 40, and 50. The compressed image test results show that increasing the threshold results in a higher compression ratio and a lower PSNR value. The PSNR obtained is also getting more significant for testing with a larger image size.

Meanwhile, testing the compression and decompression time for all test images using the Haar, Daubechies, and Biorthogonal wavelet methods shows that the compression time is faster than the decompression time. The test results on both medical images showed that the CT-scan images on Haar and Biorthogonal wavelets were the best with an average compression ratio of 40.76%, PSNR 33.77. The average compression time is 0.52 seconds, and the decompression time is 2.27 seconds. Based on the test results, this study recommends that the Daubechies wavelet USG is very good for compression, which is 0.51 seconds, and the Biorthogonal wavelet method is very good for medical image decompression, which is 1.69 seconds.

#### ACKNOWLEDGMENT

We thank the Politeknik Negeri Bali Center for Research and Community Service for supporting the grand research as well as the research team from Universiti Sains Malaysia and INSTIKI.

#### REFERENCES

- [1] Cinaglia, P., D. Mirarchi, and P. Veltri, "Information Retrieval in Life Sciences", in *Encyclopedia of Bioinformatics and Computational Biology*, S. Ranganathan, et al., Editors. 2019, Academic Press: Oxford. p. 1104-1108.
- [2] Jinguo, W., W. Na, and M. Haichun, "Application of computer technology in medical image processing". in *Proceedings of the 4th International Conference on Information Technology and Management Innovation*. 2015. Atlantis Press.
- [3] Placidi, G., "Adaptive compression algorithm from projections: application on medical greyscale images". *Computer in Biology and Medicine*, 2009. 39(11): p. 993-999.
- [4] Baeza, I., et al., "ROI-based procedures for progressive transmission of digital images: A comparison". *Mathematical and Computer Modelling*, 2009. 50(5): p. 849-859.
- [5] Masarwa, S., O. Kreichman, and S. Gilaie-Dotan, "Larger images are better remembered during naturalistic encoding". *Proceedings of the National Academy of Sciences*, 2022. 119(4): p. e2119614119.
- [6] Lee, S.-W. and H.-Y. Kim, "An energy-efficient low-memory image compression system for multimedia IoT products". *EURASIP Journal on Image and Video Processing*, 2018. 2018(1): p. 87.
- [7] Parmar, C., "A Review of Image Compression", 2012.
- [8] Kaur, R. and Pooja, "A Review of Image Compression Techniques". *International Journal of Computer Applications*, 2016. 142: p. 8-11.
- [9] Singh, M., et al., "Various Image Compression Techniques: Lossy and Lossless". *International Journal of Computer Applications*, 2016. 142: p. 23-26.
- [10] Pl, C. and A. Tamilmathi, "Effective lossy and lossless color image compression with Multilayer Perceptron". *International Journal of Engineering and Technology(UAE)*, 2018. 7: p. 9-14.
- [11] Lakshmi, N.A., "Lossy Image Compression Techniques". *American Journal of Computer Science and Information Technology*, 2021. 9(7).
- [12] Hu, Y., et al., "Learning End-to-End Lossy Image Compression: A Benchmark". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022. 44(8): p. 4194-4211.
- [13] Ayoobkhan, M.U.A., E. Chikkannan, and K. Ramakrishnan, "Lossy image compression based on prediction error and vector quantisation". *EURASIP Journal on Image and Video Processing*, 2017. 2017(1): p. 35.
- [14] Md. A. Rahman and M. Hamada, "Lossless Image Compression Techniques: A State-of-the-Art Survey," *Symmetry*, vol. 11, no. 10, p. 1274, Oct. 2019, doi: 10.3390/sym11101274.
- [15] Xin, G. and P. Fan, "A lossless compression method for multi-component medical images based on big data mining". *Scientific Reports*, 2021. 11(1): p. 12372.
- [16] Bull, D.R. and F. Zhang, "Chapter 7 - Lossless compression methods", in *Intelligent Image and Video Compression (Second Edition)*, D.R. Bull and F. Zhang, Editors. 2021, Academic Press: Oxford. p. 225-270.
- [17] Singh, U. and M. Kumar, "A Review: Compression on Medical Images". *International Journal of Engineering and Technical Research*, 2022. Vol. 11: p. 103-109.
- [18] Rojas-Hernández, R., et al., "Lossless Medical Image Compression by Using Difference Transform". *Entropy (Basel)*, 2022. 24(7): p. 951.
- [19] Nagaria, B., M.F. Hashmi, and P. Dhakad, "Comparative Analysis of Fast Wavelet Transform for Image Compression for optimal Image Quality and Higher Compression Ratio". *International Journal of Engineering Science and Technology*, 2011. 3.
- [20] Gaber, R., et al., "Image Compression Using High Level Wavelet Transformer with Non-Uniform Quantizer and Different Levels Huffman Codes". *IOP Conference Series: Materials Science and Engineering*, 2020. 765: p. 012072.
- [21] Kharate, G.K. and V.H. Patil, "Color Image Compression Based On Wavelet Packet Best Tree ". *International Journal of Computer Science (IJCS)*, 2010. 7(2): p. 31-35.
- [22] Nagarajan, A. and K. Alagarsamy, "An enhanced approach in run length encoding scheme (EARLE)". *International Journal of Engineering Trends and Technology*, 2011: p. 43-48.
- [23] Sahooinst, R., S. Roy, and S.S. Chaudhuri, "Haar Wavelet Transform Image Compression Using Various Run Length Encoding Schemes". 2015. Cham: Springer International Publishing.
- [24] Xizhi, Z., "The Application of Wavelet Transform in Digital Image Processing"2009. 326-329.
- [25] Dumitrescu, D. and C.-A. Boiangiu, "A Study of Image Upsampling and Downsampling Filters". *Computers*, 2019. 8(2): p. 30.
- [26] Urban, K., "257Wavelets on General Domains", in *Wavelet Methods for Elliptic Partial Differential Equations*2008, Oxford University Press. p. 0.
- [27] Kalavathi, P. and S. Boopathiraja, "A Wavelet Based Image Compression with RLC Encoder". *Computational Methods, Communication Techniques and Informatics*, 2017: p. 289-292.
- [28] Weisz, F., "The Inverse of the Continuous Wavelet Transform". 2018. Cham: Springer International Publishing.
- [29] Rosida Vivin, N., et al., "Image Segmentation of Cows using Thresholding and K-Means Method". *International Journal of Advanced Engineering, Management and Science*, 2017. 3(9).

- [30] Cheddad, A., et al., "Digital image steganography: Survey and analysis of current methods". *Signal Processing*, 2010. 90(3): p. 727-752.
- [31] Gibson, J., "Rate Distortion Functions and Rate Distortion Function Lower Bounds for Real-World Sources". *Entropy*, 2017. 19(11): p. 604.
- [32] Mohindru, P. and Pooja, "Comparative Analysis of Haar, Daubechies and Bior wavelets on Image Compression using Discrete Wavelet Transform". 2022.
- [33] Mishra, V., A. Kumar, and A.K. Jaiswal, "Performance Comparison of Daubechies, Biorthogonal and Haar Transform for Grayscale Image Compression". *International Journal of Computer Applications*, 2015. 126: p. 40-42.
- [34] Singh, S. and S.S. Dwivedi, "Region of Interest Based Lossless and Lossy Compression for Digital Images ". *International Journal of Engineering and Technical Research (IJETR)*, 2018. 8(5): p. 16-21.
- [35] Ayu Jati, P., et al., "Planar scintigraphy image de-noising using coiflet wavelet". *Jurnal Iptek Nuklir Ganendra*, 2021. 24(2): p. 75-83.
- [36] Shaik, A. and V. Thanikaiselvan, "Comparative analysis of integer wavelet transforms in reversible data hiding using threshold based histogram modification". *Journal of King Saud University - Computer and Information Sciences*, 2021. 33(7): p. 878-889.
- [37] Darwis, D., N. Pamungkas, and W. Wamiliana, "Comparison of Least Significant Bit, Pixel Value Differencing, and Modulus Function on Steganography to Measure Image Quality, Storage Capacity, and Robustness". *Journal of Physics: Conference Series*, 2021. 1751: p. 012039.
- [38] G Nath, A., M. S. Nair, and J. Rajan, "Single Image Super Resolution from Compressive Samples Using Two Level Sparsity Based Reconstruction". *Procedia Computer Science*, 2015. 46: p. 1643-1652.
- [39] Zanaty, E. and S. Ibrahim, "High Efficient Haar Wavelets for Medical Image Compression", 2020. p. 547-557.
- [40] Tackie Ammah, P.N. and E. Owusu, "Robust medical image compression based on wavelet transform and vector quantization". *Informatics in Medicine Unlocked*, 2019. 15: p. 100183.
- [41] Bruylants, T., A. Munteanu, and P. Schelkens, "Wavelet based volumetric medical image compression". *Signal Processing: Image Communication*, 2015. 31: p. 112-133.