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Comparison of the Packet Wavelet Transform Method for Medical Image Compression

I Made Ari Dwi Suta Atmaja [a,*], Wilfridus Bambang Triadi [b], I Nyoman Gede Arya Astawa [a], Made Leo Radhitya [c]

[a] *Department of Electrical Engineering, Politeknik Negeri Bali, South Kuta, Badung, 80361, Indonesia*
[b] *School of Computer Sciences, Universiti Sains Malaysia, Penang, 11700, Malaysia*
[c] *Department of Informatics, Institut Bisnis dan Teknologi Indonesia,South Denpasar, Denpasar, 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 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.**

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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.

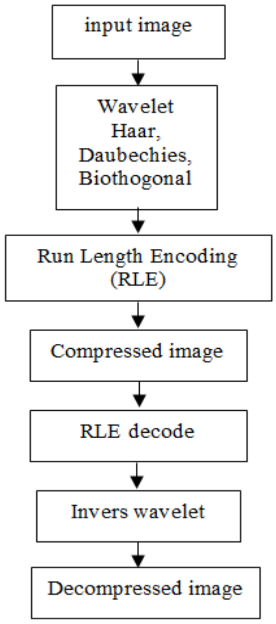

Fig. 1 System flow chart

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×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:

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

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:

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

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.

$$Bit\ rate = \frac{Js}{Is}\ bpp \quad (4)$$

Js is the compressed image file size and *Is* 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.

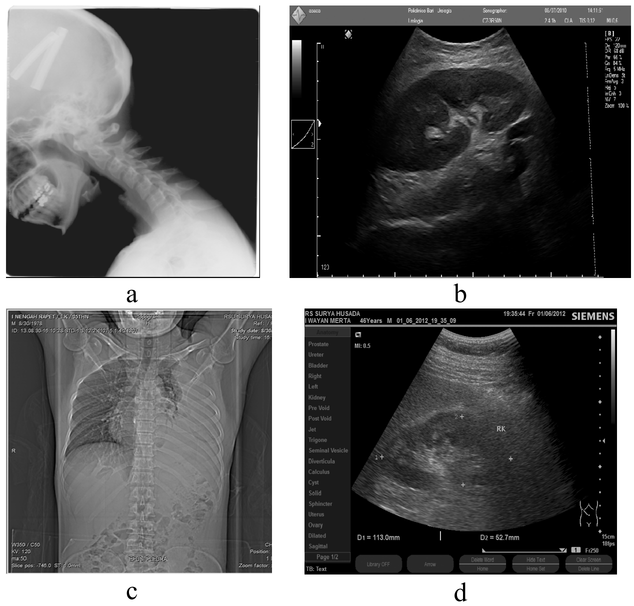

Fig. 2 (a) test image 1, (b) test image 2, (c) test image 3, (d) test image 4

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.

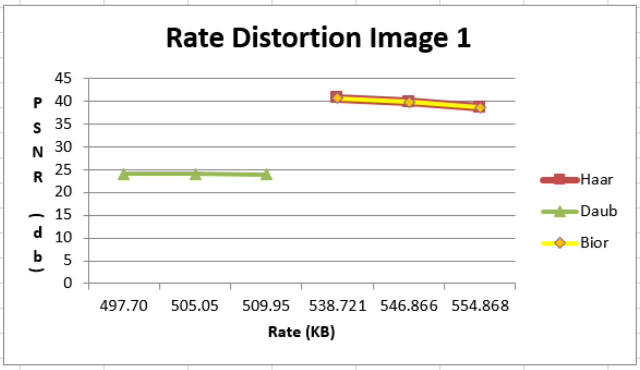

Fig. 3 Rate Distortion in test image 1

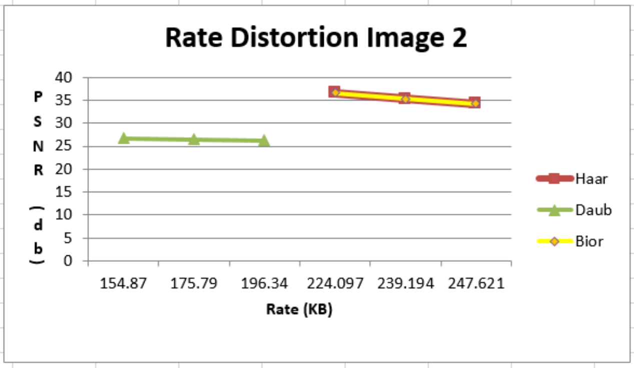

Fig. 4 Rate Distortion in test image 2

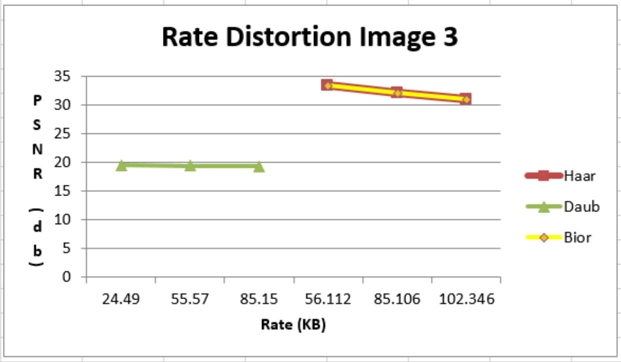

Fig. 5 Rate Distortion in test image 3

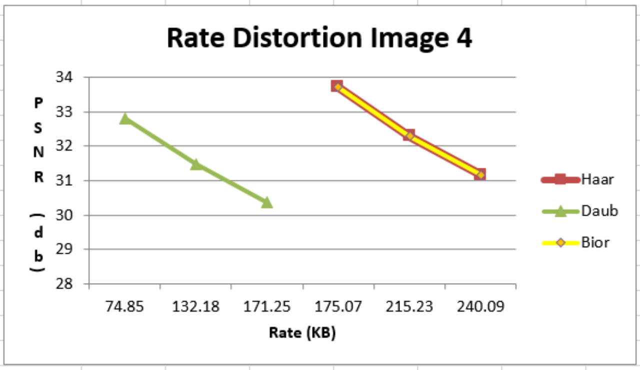

Fig. 6 Rate Distortion in test image 4

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.

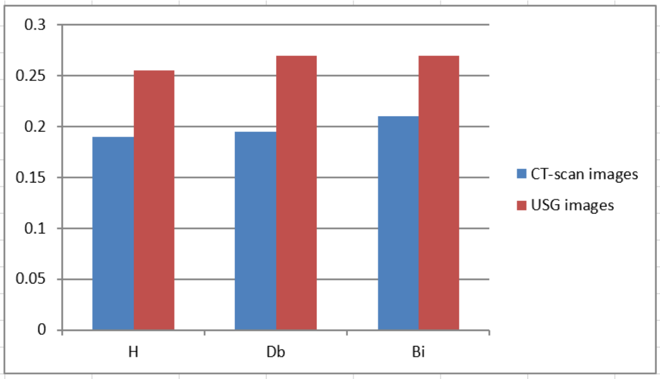

Fig. 7 The results of testing the compression time on wavelets.

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.

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