Journal of Engineering Science and Technology
Vol. 17, No. 1 (2022) 0391 - 0403

RLC - BASED IMAGE COMPRESSION USING WAVELET DECOMPOSITION WITH ZERO - SETTING OF UNNECESSARY SUB-BANDS

AKRAM ABDUL MAWJOOD DAWOOD[1,*],
AZHAR SABAH ABDULAZIZ[2], ALNAWAR JASSIM MOHAMMED[3]

[1]Department of Computer Engineering, College of Engineering, University of Mosul, Mosul, Iraq
[2]Department of Computer and Information Engineering, College of Electronic Engineering, Ninevah University, Mosul, Iraq
[3]Department of Control and Computer, College of Engineering, Almaaqal University, Basrah, Iraq
*Corresponding Author: akram.dawood@uomosul.edu.iq

Abstract

Image compression is a vital approach that is used in different applications. Transformation lossy compression is necessary as communication speed and storage are limited. Many of image compression techniques rely on thresholding the transformation coefficients to reduce the compressed image size. In this paper, the coefficients of specific bands of the wavelet transform are abstracted. In the proposed approach, 2-D matrices are abstracted into a single value. Throughout the conducted experiments, it is noticed that the discrete wavelet transform (DWT) bands have zero-mean Gaussian distributed histogram, except the approximation sub-band. Hence, estimating the power of those 'unnecessary' bands will be enough to re-construct the image with less errors. Ignoring the coefficients of the unnecessary bands by abstracting them to a single value for each, is like resetting them. The achieved data reduction is high as compared to the image quality at the construction. It is proved that the proposed Abstract and Reset Unnecessary DWT Bands (ARUBA) has better compression ratio compared to the standard JPEG2000.

Keywords: Image compression, JPEG2000, Signal processing, Standard deviation, Wavelet transform.

1. Introduction

Although image lossy compression degrades the compressed image regarding the original, it was continuously investigated. Some levels of quality, loss is acceptable for many applications when the bit rate reduction is the target. Besides, the objective loss of an image might not decrease the subjective image quality, due to the nature of human visual system. In applications like video communications, video surveillance, and motion estimation, losing some objective image quality while improving data rate reduction is recommended.

The transformation-based compression technique is one of the effective approaches. The standard Joint Photographic Experts Group (JPEG) is based on the discrete cosine transform (DCT). The later version of it, JPEG2000, relies on the discrete wavelet transform (DWT) instead. The transformation compression techniques are basically performed in three stages, the image transformation followed by quantization and then coding, usually entropy coding is common.

Currently, DWT is dominant in image compression as it supports image progressive features in data transmission [1, 2]. Gradually, DWT is becoming more efficient performance and lower computation costs as it was adopted in the JPEG2000 standard. Hence, most researchers investigate the quantization/thresholding and coding stages after the DWT [3, 4].

The following section summarises some approaches that used the transformation compression based on DWT. In Section 3, some wavelet transform properties are overviewed and Section 4 discusses the proposed algorithm. Experimental results are listed in Section 5. Finally, Section 6 concludes this paper.

2. Related Work

This section is dedicated to investigating the DWT related transformation compression that has been developed over the years. Setia and Kumar [5] improved compression rate by introducing specific quantization that enables the concurrent coding steps to work efficiently. After applying DWT using Haar filter, the sub-bands coefficients are grouped based on their levels, and then quantized. The run-length coding (RLC) followed by entropy coding are both used in the final stage. Although these steps are implemented in the JPEG2000 standard, dividing DWT coefficients into multiple groups changed the results. Better results were reported for lower compression rate, or higher bit-per pixel (BPP), however, the upturn was in the performance for coloured images [5].

The DWT coefficient grouping followed by compressive sensing (CS) was used for further improvement. by Qureshi and Deriche [6], The coefficients were re-arranged in ‘sparse vectors’, and used as an input to the CS. A random Gaussian matrix was generated to assign the higher weights to lower frequency. The reported peak signal-to-noise ratio (PSNR) was 37.77 dB for 0.5 BPP, competing other CS based methods at that time [6].

The automatic thresholding using particle swarm optimization (PSO) was introduced by Ahmadi et al. [7], in which, for each sub-band, the entropy was reduced before handing information to an RLC, and hence more efficient compression was noticed as compared to fixed threshold approach. The reported PSNR was between 37.91 dB and 38.23 dB for 3 to 5 levels of decomposition, respectively for Lena image with 0.5 BPP. A hybrid compression approach that is based on polynomial approximation is suggested by Al-Khafaji et al. [8].

The polynomial approximation was applied after 2 levels of DWT and followed by bit-lane slice coding, LZW, RLC and Huffman coding. The reported compression ratio was 45.45 with 32.67 dB PSNR for Lena image. The 2-D coefficients layers, that were divided into smaller matrices, were coded using the improved RLC (I-RLC) [9]. This technique improves the processing speed, and hence gave the processor a time to process more information. Despite the high compression ratio, the reported PSNR was remarkably degraded. Automatic thresholding using PSO was given another chance [10], while a pre-processing step was introduced this time.

The Haar filter coefficients in DWT were optimized and RLC coder was used. Researchers claimed to obtain better results as compared to other traditional techniques. In satellite image processing, a 3-D DWT decomposition followed by Huffman coding and thresholding was investigated. The results were promising using this technique as compared to existing methods regarding LANDSAT images [11].

Khan et al. [12] conducted to modify JPEG compression for manufacturing process. The suggested modification was to replace DCT by Haar wavelet transform (HWT). According to the researchers, the HWT works more efficient with the run-length code (RLC) than with the DCT [12].

3. Wavelet Transform Overview

The wavelet transform is representing any signal, like the image signal, as a group of wavelets that are localized in both frequency and time. In image signals, the wavelet decomposition, i.e., transform, leads to obtaining two wavelet types, low and high frequency waveforms. The low frequencies are corresponding to the smooth parts of the image, also known as scaling function Φ. While the wavelet that stands for the high frequencies, known as the mother wavelet function Ψ, preserving the details of the image [13]. Using appropriate low-pass filter coefficients $h_L(k)$, the scaling function is estimated by solving the following two-scale dilation equation [3, 14]:

$$\Phi(x) = \sum_k h_L(k)\Phi(2x - k) \tag{1}$$

where x is the input signal, and k is an integer so that $k \in \mathbb{Z}$. The related mother wavelet Ψ is then defined as:

$$\Psi(x) = \sum_k h_H(k)\Phi(2x - k) \tag{2}$$

where $h_H(k)$ is for the high-pass filter coefficients.

Both Eqs. (1) and (2) represent convolution of the scaled input with low-pass and high-pass filters. The results are decimated by the factor of two, i.e., down sampled by 2 [15]. The DWT decomposition can be represented as four-channel of 2-D filter-bank, with low and high pass filters at each branch as shown in Fig. 1. The four sub-bands are corresponding to the filter that it passed though, starting from Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH).

The crucial criteria of selecting the suitable wavelet functions are the compactness support, the number of vanishing moments, the symmetry, the consistency, and the degree of smoothness. The DWT filters are designed according to the desired criteria and specifications [16]. The Daubechies Wavelet (DW) is an example of the orthogonal wavelet family that supports compactness. The high and low pass filters are efficiently implemented using finite-impulse response (FIR) systems. The main disadvantage of DW is that it adds artifact as it does not support symmetry [3]. However, DW shows better results in image compression through the conducted experiments in this paper.

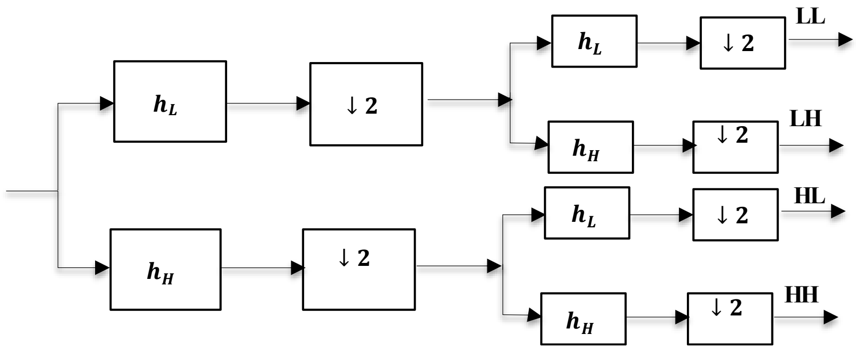


Fig. 1. Filter-Bank for 1 stage DWT.

4. The proposed Abstract and Reset Unnecessary Bands Algorithm (ARUBA)

A lossy compression that is based on image transformation is a popular approach. The Discrete wavelet transform (2-D DWT) followed by quantization, threshold, and coding is becoming a standard for JPEG2000. Subsequently, different approaches have been applied on quantization and coding to improve compression. In such a way, 2-D DWT is kept as it supports the progressive feature of image transmission [3].

4.1. ARUBA compression

The proposed methodology in this work relies on resetting specific layers rather than thresholding their values. Later, a floating point quantizer is introduced to facilitate the inverse (2-D DWT) at decompression. Instead of thresholding the sub-bands coefficients as in JPEG2000, only their standard deviation is considered. It means that only the approximation sub-band coefficients are preserved, and the other sub-bands are abstracted to a single value. The main steps of the proposed Abstract and Reset Unnecessary Bands algorithm (ARUBA) are depicted in Fig. 2.

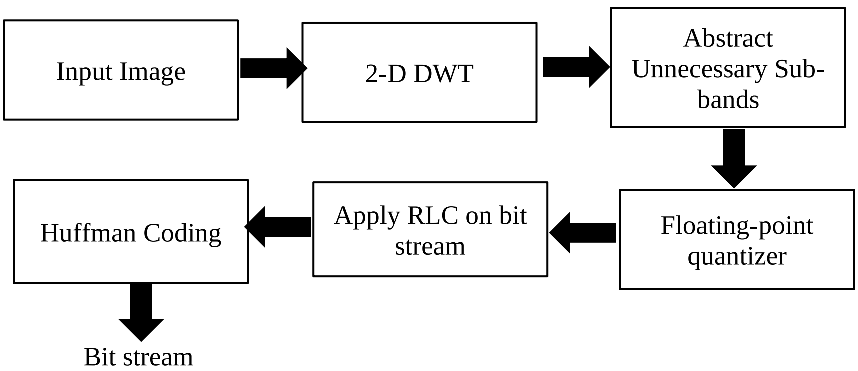
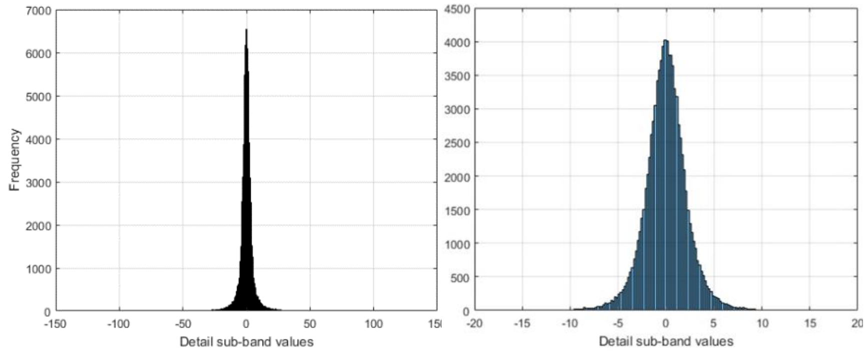
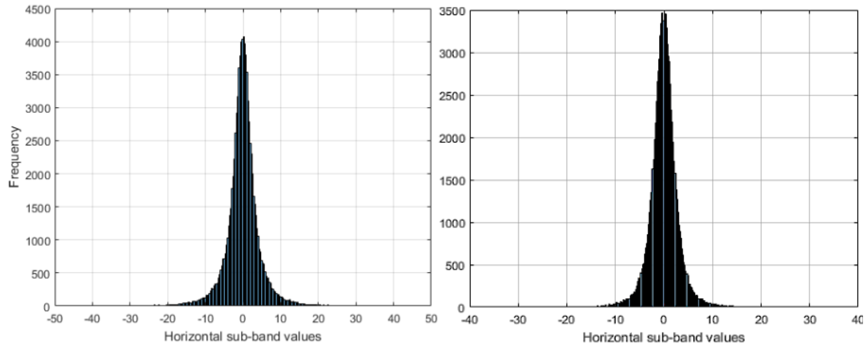


Fig. 2. Overview of the proposed ARUBA image compression.

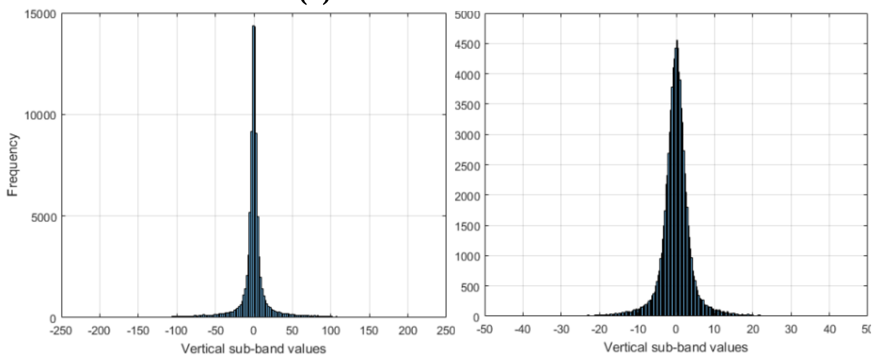
Daubechies wavelets were chosen for ARUBA, as it showed better performance through the conducted experiments. The so called 'unnecessary' bands are basically the horizontal, vertical and the detail (HVD) sub-bands, which are resulted from the (2-D DWT) transformation. It is noticed that the coefficients distribution of each one of those sub-bands has specific properties. By inspecting the distribution of the unnecessary sub-bands, it can be concluded from Fig. 3 that they all have a bell-shape distribution, also known as Gaussian distribution. Besides, each test image has a distinctive standard deviation value (σ).



(a) Detail sub-band



(b) Horizontal sub-band



(c) Vertical Sub-band

Fig. 3. The unnecessary sub-bands distributions for Barbara on the left and Lena on the right.

The unnecessary HVD sub-bands are abstracted by estimating their standard deviation values. The standard deviation of sub-band B σ_B, is measured as follows:

$$\sigma_B = \sqrt{\frac{1}{(N-1)(M-1)} \sum_{i=1}^{N} \sum_{j=1}^{M} |B(i,j) - \mu|^2} \tag{3}$$

and

$$\mu = \frac{1}{N \times M} \sum_{i=1}^{N} \sum_{j=1}^{M} B(i,j) \tag{4}$$

where μ is the 2-D mean and B represents the sub-bands as $B = \{h, v, d\}$ stands for horizontal, vertical, and diagonal sub-bands, respectively.

It is noticed that the 2-D wavelet transformation produces floating point matrices for each sub-band. Removing the fractions of the DWT approximation layer will increase the error at the end. Therefore, it is proposed to maintain the DWT coefficients as they are, especially if only the approximation sub-band is maintained. Hence, a floating-point quantizer is introduced to quantize the approximation sub-band, while the HVD sub-bands are substituted by their standard deviations. The floating-point quantizer is merely a floating-point decimal-to-binary converter, and its output is controlled by the desired resolution of the integer and the fraction part of the number.

Finally, a running-length coder (RLC) followed by, and the entropy encoder (Huffman encoder) are used to reduce redundancy of the final bit stream. Both the approximation sub-band and the standard deviation values of the unnecessary bands are encoded in this step.

4.2. ARUBA decompression

In the decompression process, Huffman and RLC decoders are trying to reverse the coding of ARUBA compression in binary level. Then, the binary values are converted into floating-point numbers that represent the approximation sub-band that is decomposed using DWT, as well as the abstraction of the other three sub-bands. Remember that the vertical, horizontal and the detail sub-bands are approximated to a single value for each. It is interesting that the three unnecessary bands are easily constructed using the estimated standard deviations during the compression step. The approximation band, side by side with the reconstructed bands, are used to reconstruct the image back again using inverse 2-D discrete wavelet transform (IDWT). The decompression steps of the proposed ARUBA algorithm are shown in Fig. 4.

The unnecessary sub-bands reconstruction is basically generating 2-D zero-mean Gaussian distributed random signals $\mathcal{N}(0, \sigma_B^2)$, where $B = \{v, h, d\}$. Three sub-bands are constructed, and with the approximation sub-band are used in the IDWT process to re-construct the image. Finally, a post-processing is required to further improve the image and reduce the decompression error.

A powerful edge detector is suggested to be used in the post processing for proposed ARUBA. because no pre-processing operations are used in the encoder. Hence, Canny edge detector is preferred in this case because it is a combination of a Gaussian filter followed by a first order differentiator [17]. Through the post-processing step, the IDWT output is passed through Canny edge detector followed by a 2-D median filter, as shown in Fig. 5.

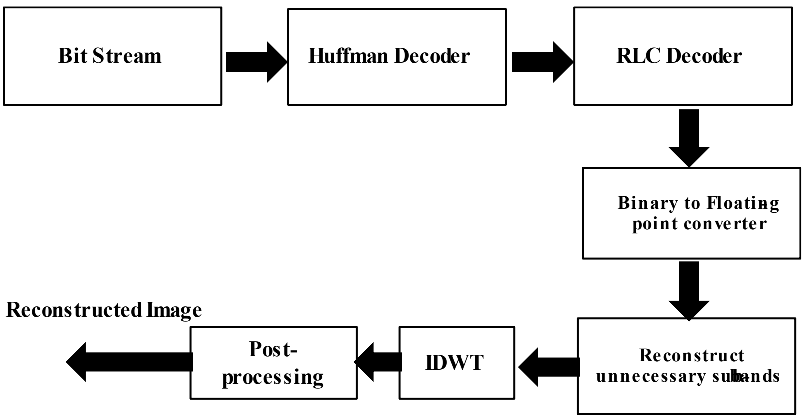


Fig. 4. Overview of ARUBA decompression stages.

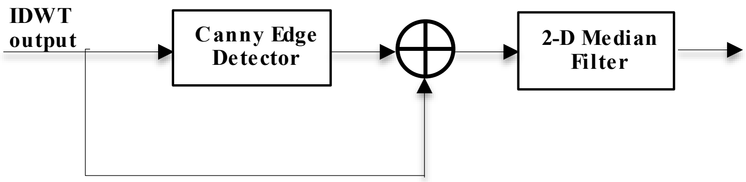


Fig. 5. ARUBA Post-processing.

5. Experimental Results

Many levels of DWT decompositions are experimented in this work. The conducted experiments are evaluated using bit per pixel (BPP), compression ratio (CR) and peak signal-to-noise ratio (PSNR). While the first and the second metrics measure the compression capability of the algorithm, the third one is related to the recovered image quality [18].

The BPP is the ratio of total bits in the compressed image divided by the total bits in the original one, or:

$$BPP = \frac{\text{Total bits in Compressed Image}}{\text{Total pixels in original Image}} \tag{5}$$

The compression ratio (CR) is:

$$CR = \frac{\text{Uncompressed Image Size}}{\text{Compressed Image Size}} \tag{6}$$

The PSNR is the ratio between the maximum possible power of the image signal and the mean square error (MSE). It is more convenient to measure PSNR in dB as follows [6, 7, 19]:

$$PSNR = 10 \times \log_{10}\left(\frac{MAX_i^2}{MSE}\right) \tag{7}$$

where $MAX_i = 255$ which is the maximum intensity value of the image, which is considered for 8-bit resolution in the gray image. The MSE is estimated as follows:

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[I(x,y) - I_c(x,y)]^2 \tag{8}$$

so that I is the original image and I_c is the recovered image after decompression. The bit per pixel (BPP), the compression ratio (CR) and the peak signal-to-noise ratio (PSNR) in dB are listed in table 1 according to each DWT decomposition level.

Table 1. Compression ratio (in BPP) vs. PSNR (in dB) for ARUBA compression.

Image	DWT Decomposition Level	BPP	CR	PSNR (dB)
Lena 512X512	1	0.63	12.7	39.82
	2	0.30	26.67	35.56
	3	0.16	50	32.20
	4	0.12	66.67	29.71
	5	0.09	88.89	28.57
Barbara 512X512	1	0.68	11.76	33.77
	2	0.31	25.81	30.81
	3	0.18	44.44	29.31
	4	0.12	66.67	28.44
	5	0.10	80	28.08
Baboon 256X256	1	0.87	9.19	32.50
	2	0.53	15.09	31.43
	3	0.39	20.51	30.46
	4	0.34	23.53	29.87
	5	0.31	25.81	29.33

The subjective results of the proposed ARUBA algorithm for Lena and Barbara images with five levels 2-D DWT decompositions are shown in Figs. 6 and 7 respectively, where the sizes of those image are 512X512 pixels.

Fig. 6. The results of Lena image with different levels.

Fig. 7. The subjective results of Barbara image with different levels.

The BPP versus the PSNR of the proposed ARUBA technique is compared to EZW, SPIHT, SPECK and JPEG2000, for Lena and Barbara images, with size 512×512 as shown in Fig. 8.

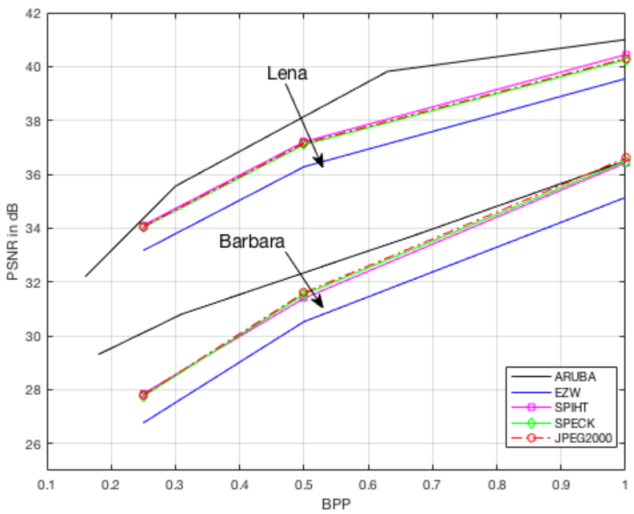


Fig. 8. Comparing ARUBA with different approaches for Lena and Barbara images. Results of other methods are based on [3].

For Lena image, SPIHT coding technique outperform all approaches except the suggested ARUBA. However, PSNR obtained by ARUBA for Barbara image is better for lower BPP, while in higher BPP (lower compression rate) JPEG2000 is comparable to ARUBA.

The simulation results are obtained using MATLAB R2017a on Intel(R) core i5 processor operating at frequency of 1.6 GHz having RAM of size 4 GB. The proposed ARUBA compression time, for test image Lena, was compared to the improved fractal SPIHT algorithm proposed by Anu and Sahu [20], as shown in Fig. 9.

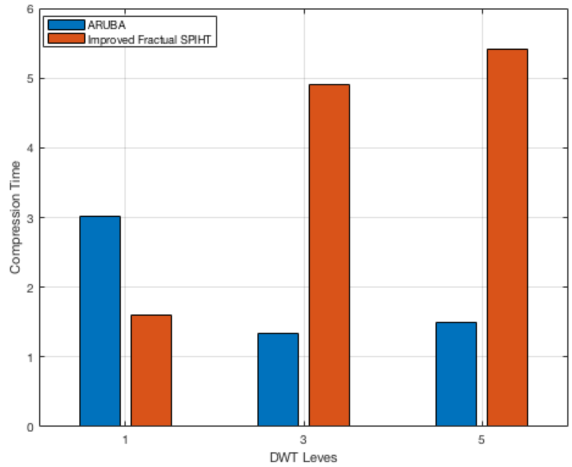


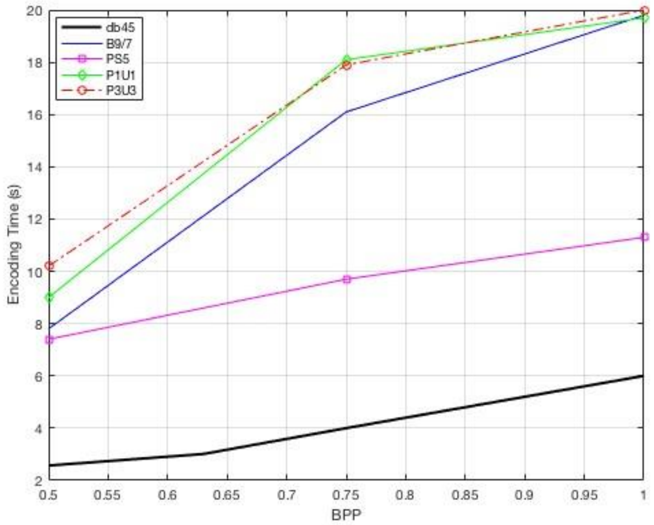
Fig. 9. Compression time vs. various DWT levels for ARUBA and the improved fractal SPIHT.

The compression time for one level SPIHT was 11.42 seconds, while the improved fractal SPIHT was superior by taking 1.6 seconds for encoding [20]. The proposed ARUBA took 3.01 seconds for the first level, however the encoding time decreased for higher levels DWT. So, the proposed algorithm outperforms the modified SPIHT on average. The ARUBA time performance for different DWT levels is listed Table 2.

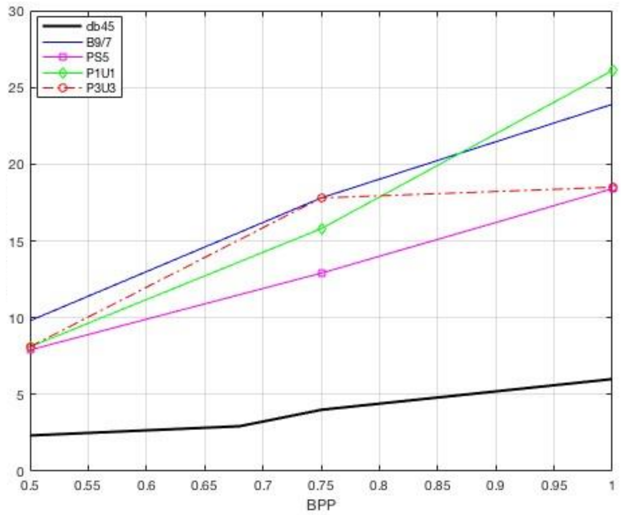
Table 2. Computation time in for each step in ARUBA in seconds.

	Level	DWT	Huffman	RLC	Total
Lena (512X512)	1	0.34	2.47	0.2	3.01
	2	0.53	1.28	0.08	1.89
	3	0.63	0.67	0.04	1.34
	4	0.88	0.52	0.02	1.42
	5	1.01	0.47	0.02	1.5
Barbara(512X512)	1	0.52	2.26	0.15	2.93
	2	0.54	1.08	0.07	1.69
	3	0.61	0.65	0.03	1.29
	4	0.73	0.56	0.03	1.32
	5	0.92	0.47	0.02	1.41
Baboon(256X256)	1	0.37	0.84	0.06	1.27
	2	0.62	0.55	0.04	1.21
	3	0.53	0.49	0.02	1.04
	4	0.78	0.39	0.02	1.19
	5	0.92	0.4	0.02	1.34

In the proposed ARUBA, Daubechies (db45) filter is used in 2-D DWT decomposition, while the filter B9/7 is usually used in JPEG2000. Therefore, we compared the encoding time with the most common filters used for DWT in image compression as listed in [3], as shown in Fig. 10. It is noticed that db45 consumed less time as compared to other filter types. Which leads to the conclusion that the ARUBA overcomes JPEG2000 in encoding time.



(a). Lena



(**b). Barbara**

Fig. 10. Encoding time vs. BPP for different DWT filters.

6. Conclusion

The suggested approach is based on the idea that three of the four sub-bands, resulting from DWT, could be abstracted. The amount of information in the four sub-bands, that are resulted from DWT, can be reduced through thresholding and coding. Thresholding and proper encoding algorithms are considered as standard in image compression, specifically after standardizing JPEG2000.

The argument of this paper is that considerable data reduction has been obtained by resetting some bands, called unnecessary bands. However, the conducted experiments have shown that resetting the horizontal, vertical and the detail sub-bands significantly increases the compression loss. Meanwhile, it has been noticed that the values of the DWT 'unnecessary' HVD sub-bands, possess zero-mean normal distributions. Therefore, the HVD sub-bands have been abstracted to a single value, which is the standard deviation only.

Eventually, those unnecessary HVD bands have been easily re-generated using a random number generator that can produce Gaussian distributed 2-D signals using certain standard deviation. The abstraction, and then resetting of the unnecessary bands algorithm (ARUBA), has save a great amount of data and hence reducing bit per pixel (BPP). Besides, the results, from the PSNR point of view, have appeared promising.

Further study and analysis of the nature of the HVD sub-bands can lead to improve the ARUBA approach. The re-generating process of the HVD unnecessary bands can be elaborated and enhanced in the future for better performance and quality improvement.

References

1. Al-Kishawi, S.A.; Abdul-Jabbar, J.M.; and Ali, Q.I. (2020). Design and relaization of less-complex wavelet-based transceivers. *Journal of Engineering Science and Technology* (*JESTEC*), 15(2), 1155-1116.
2. Jasim, A.M.; Abd, H.M.and Abdul-Jabbar, J.M. (2020). Complexity reduction of slantlet transform structure based on the multiplierless realization. *Journal of Engineering Science and Technology* (*JESTEC*), 15(3), 1705-1718.
3. Boujelbene, R.; Jemaa, Y.B.; and Zribi, M. (2019). A comparative study of recent improvements in wavelet-based image coding schemes. *Multimedia Tools and Applications*, 78(2), 1649-1683.
4. Boujelbene, R.; Jemaa, Y.B.; and Zribi, M. (2017). An efficient codec for image compression based on spline wavelet transform and improved SPIHT algorithm. *Preceedings of* 2017 *International Conference on High Performance Computing & Simulation* (*HPCS*). Genoa, Italy, 819-825.
5. Setia, V.; and Kumar, V. (2012). Coding of DWT coefficients using run-length coding and huffman coding for the purpose of color image compression. *World Academy of Science*, *Engineering and Technology International Journal of Computer and Information Engineerin*, 6(2), 236-239.
6. Qureshi, M.A.; and Deriche, M. (2015). A new wavelet based efficient image compression algorithm using compressive sensing. *Multimedia Tools and Applications*, 75(12), 6737-6754.
7. Ahmadi, K.; Javid, A.Y.; and Salari, E. (2015). An efficient compression scheme based on adaptive thresholding in wavelet domain using particle swarm optimization. *Signal Processing: Image Communication*, 32, 33-39.
8. Al-Khafaji, G.; Al-iesawi, S.; and Rajab, M.A. (2015). A hybrid lossy image compression based on wavelet transform, polynomial approximation model, bit plane slicing and absolute moment block truncation. *International Journal of Computer Science and Mobile Computing* (*IJCSMC*), 4(6), 954-961.

9. Babu, S.A.; Eswaran, P.; and Kumar, C.S. (2016). Lossless compression algorithm using improved RLC for grayscale image. *Arabian Journal for Science and Engineering*, 41(8), 3061-3070.
10. Rajan, P.V.S.; and Fred, A.L. (2017). An efficient compound image compression using optimal discrete wavelet transform and run length encoding techniques. *Journal of Intelligent Systems*, 28(1), 87-101.
11. Boopathiraja, S.; and Kalavathi, P. (2018). A near lossless multispectral image compression using 3D-DWT with application to LANDSAT images. *International Journal of Computer Sciences and Engineering*, 6(4), 332-336.
12. Khan, S.; Nazir, S.; Hussain, A.; Ali, A.; and Ullah, A. (2019). An efficient JPEG image compression based on Haar wavelet transform, discrete cosine transform, and run length encoding techniques for advanced manufacturing processes. *Measurement and Control*, 52(9-10), 1532-1544.
13. Saroya, N.; and Kaur, P. (2014). Analysis of image compression algorithm using DCT and DWT transforms. *International Journal of Advanced Research in Computer Science and Software Engineering*, 4(2), 897-900.
14. Penedo, S.R.M.; Netto, M.L.; and Justo, J.F. (2019). Designing digital filter banks using wavelets. *EURASIP Journal on Advances in Signal Processing*, 2019, 33, 1-11.
15. ZainEldin, H.; Elhosseini, M.A. and Ali, H.A. (2015). Image compression algorithms in wireless multimedia sensor networks: A survey. *Ain Shams Engineering Journal*, 6(2), 481-490.
16. Grgic, S.; Grgic, M.; and Zovko-Cihlar, B. (2001). Performance analysis of image compression using wavelets. *IEEE Transactions on Industrial Electronics*, 48(3), 682-695.
17. Abdulaziz, A. (2017). *Image morphology and statistical analysis for number plate recognition*. Noor Publishing.
18. Boopathiraja, S.; Kalavathi, P.; and Dhanalakshmi, C. (2019). Significance of image compression and its upshots - A survey. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 5(2), 1203-1208.
19. Kalavathi, P.; and Boopathiraja, S. (2017). A wavelet based image compression with RLC encoder. *Computational Methods*, *Communication Techniques and Informatics*, 1(1), 289-292.
20. Anu, S.; and Sahu, S.S. (2019). Improved fractal-SPIHT hybrid image compression algorithm. *In proceeding of* 10*th International Conference on Computing*, *Communication and Networking Technologies* (*ICCCNT*). Kanpur, India, 1-4.