Fingerprint Image Compression using Biorthogonal and Orthogonal Wavelets at Different Levels of Discrete Wavelet Transform

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Abstract

Storage space has become a significant issue in this digital generation. Forensic applications such as criminal investigations, terrorist identification, and national security issues require large amounts of space to store large volumes of fingerprints and face recognition scans collected and stored every day. Ultimately, less memory space results to more time used to process and transmit an image. In this paper, fingerprint images are compressed using the DWT (discrete wavelet transform) biorthogonal wavelet Bior4.4 and orthogonal wavelet Haar at different levels of transformation. The experiment is recognized through python and is divided into two parts; transformation testing and SPIHT (Set Partitioning in Hierarchical Trees) algorithm compression. The peak signal to noise ratio (PSNR), mean square error (MSE) as well as the compression ratio (CR) are used to objectively enumerate the quality of the compressed images. It is observed that MSE and PSNR are favorable when transformation is done using Bior 4.4 first then Haar during the remaining levels as proposed rather than using one distinct wavelet for transformation.

Keywords: Discrete Wavelet Transform, Fingerprint Image Compression, Bior4.4, Haar Wavelet, Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR)
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1. Introduction

As technology advances in this digital age we are forced to manage massive volumes of information constantly [1], which can be challenging. Since fingerprint verification is one of the most trusted personal identification methods [1]. It plays an essential role in both forensic and civil cases. The fingerprint is among the most common biometric identifiers used to identify an individual in law enforcement and in immigration. A technique that minimizes redundancies and irrelevant image data for efficient storage and transmission without compromising the visual quality of the reconstructed image is required. That reduction technique is image compression [2]. Image data processing and storage attract costs and the costs are directly proportional to the size of data [3]. To overcome these limitations; it is crucial to apply a compression technique to a fingerprint image that will maintain the essential information needed to reconstruct the image and reduce the cost implications. Kambli, Mansi & Bhatia [6] state that image compression enhances the image by applying some algorithms or operations to these pixel values. Since a digital image is a representation of an image in terms of pixel values or intensities values [4]; the compression process allows reducing large data files into smaller files for efficiency of storage and transmission [5]. There are essentially two categories for data compression algorithms: lossy and lossless compression techniques. When using lossless compression techniques, the reconstructed image is numerically identical to the source image following compression. According to Ravichandran D et al. [7] the amount of compression that lossless compression can accomplish however, is limited since degradation is present in an image reconstruction after lossy compression compared to the original. Lossy compression means that images are compressed with a certain amount of loss, while preserving the essential characteristics of the image [3]. The distinction is important because lossy techniques are much more effective at compression than lossless methods [8]. However, since fingerprints exhibit a high energy in certain high frequency bands resulting from the ridge-valley pattern and other structures [9] a lossless compression algorithm is used in this paper. The fundamental goal of fingerprint image compression is to obtain the best possible image quality at a reduced storage, transmission and computation costs. The discrete wavelet transform (DWT) is known for giving better compression results over Discrete Cosine Transform (DCT) as it provides simultaneous space and frequency representation [3]. In this paper, biorthogonal and orthogonal wavelet are combined to compress fingerprint images as well as applying a SPIHT algorithm to enhance the overall image compression quality.

2. Related Work

The field of fingerprint image compression research has evolved over the decades. Early research in the 1990s comprises of traditional image compression algorithms such as JPEG. These algorithms were not specifically designed for fingerprint images and often resulted in loss of significant details. In the 2000s, researchers started exploring wavelet-based compression algorithms for fingerprint images. Sudhakar and Jayaraman [10] proposed a fingerprint compression scheme to obtain improved quality and higher compression ratio through multiwavelet transform. Embedded coding of multiwavelet coefficients was achieved through Set Partitioning in Hierarchical Trees Algorithm (SPIHT). According to Sudhakar et al (2006), for better performance in compression, filters used in wavelet transform have the property of orthogonality, symmetry, short support and higher approximation order which scalar wavelets do not satisfy simultaneously. Hence, the need for multiwavelets, which possess more than one scaling filters. Orthogonal wavelet filters used are not as efficient as biorthogonal wavelet because of the requirement for perfect image reconstruction. Wavelet transforms were found to be effective in capturing the unique features of fingerprints while achieving high compression however, there was still a need for improved enhanced methods.

In the early 2010s, researchers began focusing on minutiae-based compression algorithms for fingerprint images because these algorithms exploit spatial distribution of minutiae points to achieve efficient compression while preserving important details for fingerprint recognition. Kumar et al. [11] proposed a SPIHT based fingerprint compression algorithm. The set partitioning in hierarchical trees (SPIHT) is a modified version of the embedded zerotree wavelet method. It used DWT decomposition of image signal using biorthogonal and orthogonal properties of wavelets. The method achieved a compression ratio of 20:1. The SPIHT's shortcoming is the inability to preserve featured pattern of fingerprint images. Muhsen et al. [12] proposed a methodology for lossy fingerprint compression using wavelet and optimal re-quantization approach. 9/7 wavelet transform was used to decompose the image to form coefficients which were optimally re-quantized using generated codebook. The output stream of coding symbols were entropy coded using run-length encoding scheme. However, in this scheme the generation of codebook required additional computational resources for implementation. Haar wavelet gives excellent compression ratios, however, Gangwar [13] presented a fingerprint image compression technique using the Haar wavelet transform for image decomposition and found that this technique fell below international image compression standard as it excluded vital stages of quantization and entropy coding of a typical image encoder.

Considering that [20] states that biorthogonal 4.4 as a wavelet of the CDF wavelet family results in better compression and after observing the results of [14] in an experiment of haar, daubechies and biorthogonal wavelet transforms used to compress an image; the researcher has found it suitable to test the bior wavelet for this paper because their experimental results demonstrate that biorthogonal wavelet shows best result among the used wavelets. In this paper the researcher aims to combine haar wavelet and bior 4.4 wavelet transform as multiwavelet transform together with SPIHT compression as a means to enhance the quality of compressed fingerprint images. Given the above-mentioned researchers results; the properties of Haar; biorthogonal wavelets as well as SPIHT (being the modified version of the embedded zerotree wavelet method) makes a strong case for testing the overall compression quality of these methods combined.

3. General Image Compression System

A general image compression system involves three ultimate image coding stages being: transformation, quantization and entropy encoding.

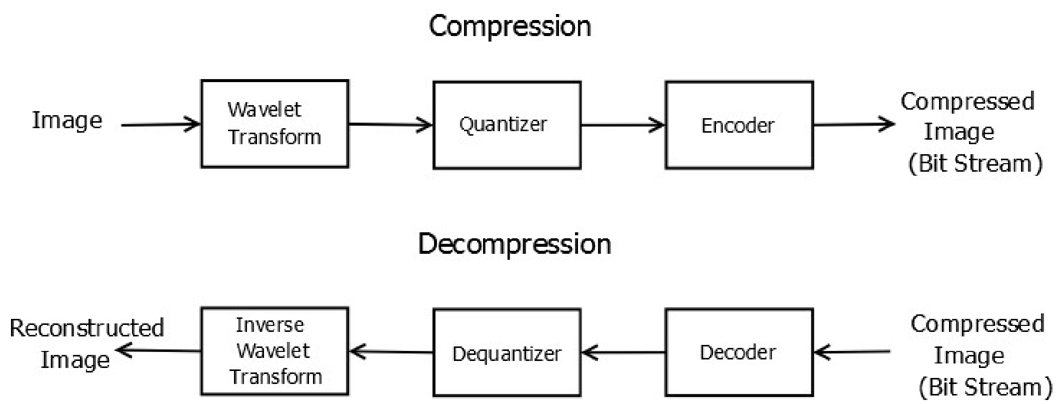

Fig. 1 Image Compression System

3.1 Transformation
To move an image into a different domain where compression will be simpler, Fourier and wavelet transforms, for example, are suitable mathematical transformation techniques that can be applied to an image. In the transform domain, it is possible to reduce the correlation level and focus the energy in a smaller area of the altered image.

3.2 Quantization
The quantization stage, which can be vector, scalar, or both, is primarily responsible for the system's "lossy" characteristics. It entails expressing the pixel values of the modified image with fewer bits—also referred to as transform coefficients. While more relevant coefficients are subjected to a finer quantization (expressed with more bits), coefficients that contribute less to the overall energy or the image's look are coarsely quantized (represented with a small number of bits) or even removed.

3.3 Entropy Encoding
Additional compression is achieved during the entropy coding step by the use of entropy coding techniques, including run-length, arithmetic, and Huffman, among others. These approaches allocate more bits to unlikely symbols and less bits to the most likely ones by taking advantage of the non-uniform distribution of symbols in the quantization result. As a result, the resulting bit-stream shrinks on average, and conversion loss is eliminated at this stage. More specifically, the wavelet transform technique fingerprint image compression methodology is applied in two steps:

(i) image encoding, which provides an optimized bit stream for the image, and
(ii) image decoding, which uses the optimized bit stream to reconstruct the image.

4. Discrete Wavelet Transform
Wavelet Transform is a type of signal representation that can give the frequency content of the signal at a particular instant of time [14]. The Discrete Wavelet Transform (DWT) decomposes a discrete signal into frequency and spatially localized sub-band components [15] making DWT one of the significant transforms used in transform-based compression due to its energy compaction in lower sub bands. Both in discrete and functional analysis, the primary advantage of a discrete wavelet transform (DWT) over a Fourier transform is its temporal resolution, which includes both location and frequency information [15]. DWT wavelets are discretely sampled than other wavelet transforms. The wavelet transform, which uses mother wavelet translations, contractions, and dilations to the input data, is a useful tool for image compression. By utilizing the data's spatial and frequency correlation, it enables multiresolution analysis, which enables the data to be applied to various scales depending on the specific details required enabling progressive transmission and image zooming without requiring extra storage [3]. Other transforms, such as the DCT, have been employed in the past to compress photos in the JPEG format, but the DWT is considered to be more superior because it decomposes the complete image at once rather than sections at a time, preventing blocking artifacts [16].

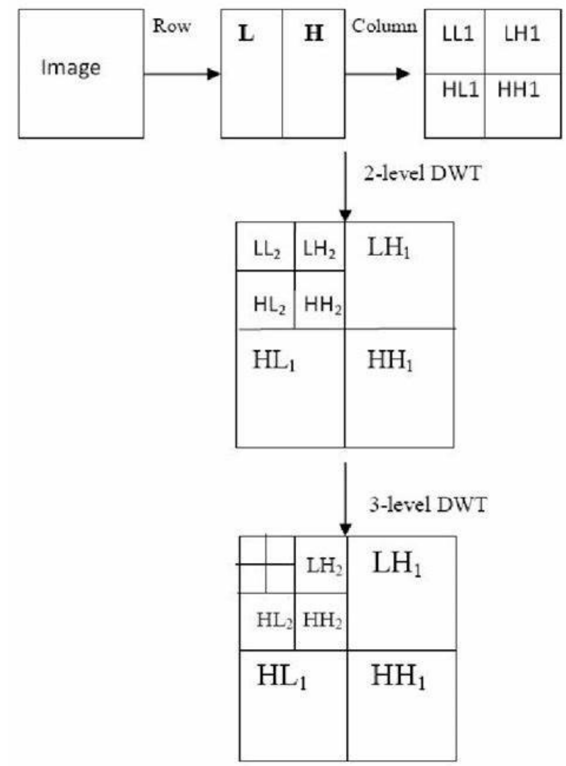

Fig. 2 Structure of wavelet decomposition at level 1, 2 & 3

The approximation sub band contains low frequency coefficients and remaining sub bands contain high frequency coefficients. Figure 1 is a two-dimensional dwt application. In DWT, the image is processed through a series of low pass filters and high pass filters. The high pass filter preserves high frequency components of the image, while the low pass filter preserves low frequency components. This operation produces two sub-images: a horizontal approximation in the low frequency region and a horizontal detail in the high frequency region. Each of these sub-images is then further processed by passing it through a low pass filter and a high pass filter along the column. Therefore, there are total four sub images –

(i) approximate image, obtained by two low pass filters (LL)
(ii) vertical detail, obtained by one low pass filter and then high pass filter (LH)
(iii) horizontal detail, by one high pass filter and a low pass filter (HL)
(iv) diagonal detail, by two high pass filters (HH). A sub-band coding technique and the formation of four sub images of the original image is shown in figure 1.

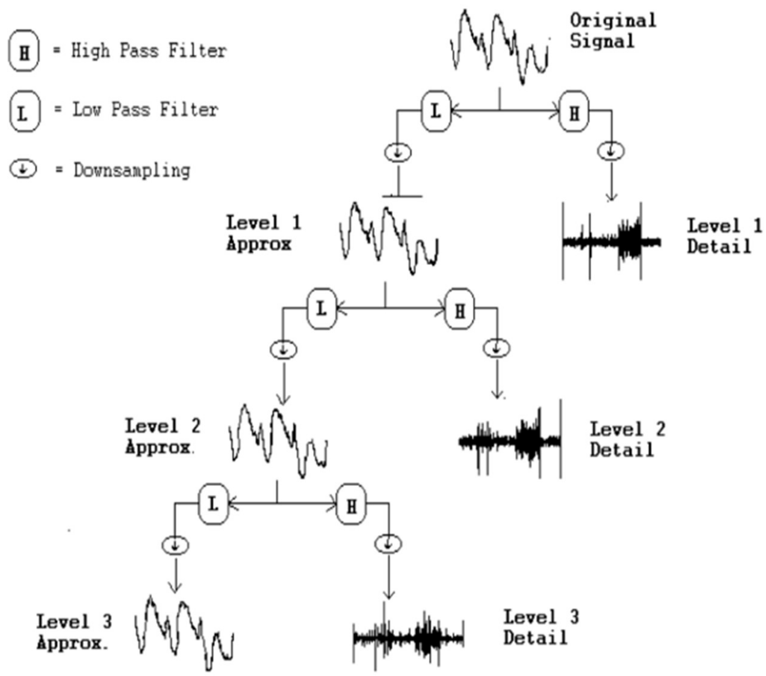

Fig. 3 Visual representation of the decomposition input source of a wavelet transformation in 3 levels

5. Biorthogonal vs Orthogonal Wavelets

Wavelet analysis is the method of choice for compressing visual signals, however, wavelets come in diverse varieties, and their characteristics alter based on a number of factors. The functions of finite energy and finite time signals are called wavelets. Two categories for the wavelets are orthogonal and biorthogonal. Support for wavelet and scaling functions, symmetry, the number of vanishing moments, regularity, orthogonality, or biorthogonality are among the primary requirements. In orthogonal wavelet, scaling and wavelet functions are orthogonal to each other resulting in complex design equations and this prevents linear phase analysis. The biorthogonal wavelet design is more flexible as the orthogonality condition is relaxed to retain linear phase characteristics.

5.1 Orthogonal Wavelet: Haar

The Haar wavelets are a sequence of functions in mathematical forms. The Haar wavelet, developed by Alfred Harr in 1990, is regarded as the quickest and most simple wavelet type [21]. It is discontinuous, like a step function, and can be computed in-place without the need for a temporary array. The values of

$$G = \left(\frac{1}{\sqrt{2}} \ \ \frac{1}{\sqrt{2}}\right) and\ H = \left(\frac{1}{\sqrt{2}} \ \ \frac{1}{\sqrt{2}}\right). \tag{1}$$

indicate the high-pass and low-pass filters which are the shortest possible wavelet filters.

$$Mother\ Wavelet\ \left(\varphi(n)\right) = \begin{cases} 1 & 0 \le n \le \dfrac{1}{2} \\ -1 & \le n \le 1 \\ 0 & otherwise \end{cases}. \tag{2}$$

This wavelet is of rectangular nature and is the only wavelet that is both symmetrical and orthogonal [17]. With only one vanishing moment; the structure of the Haar wavelet is shown in Figure 4.

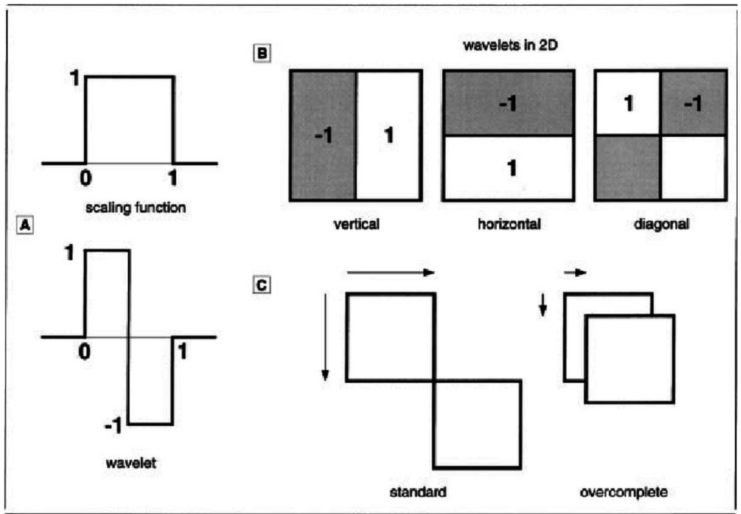

Fig. 4 Haar wavelet framework

The Haar wavelet framework; (a) the Haar scaling function and wavelet, (b) the three types of 2-dimensional non-standard Haar wavelets: vertical, horizontal, and diagonal, and (c) the shift in the standard transform as compared to our quadruple dense shift resulting in an overcomplete dictionary of wavelets. The filter coefficients to obtain Haar wavelet are shown in the Table 1.

Table 5: Filter Coefficients of Haar Wavelet

	Analysis		Synthesis	
n	Low pass filter	High pass filter	Low pass filter	High pass filter
0	0.7071	-0.7071	0.7071	0.7071
1	0.7071	0.7071	0.7071	-0.7071

The Haar wavelet is the only symmetric, finite length, orthogonal wavelet with the support interval is equal to one [22]. The Haar wavelet may not be able to detect the large changes in the input data due to less support interval. So, it is required to design symmetric filters with support interval more than two.

The biorthogonal wavelet has linear phase characteristics which are required for image reconstruction. It uses two wavelets, that is one wavelet for decomposition and another wavelet for reconstruction [18] The decomposition filter is also known as analysis filter and the reconstruction filter is also known as synthesis filter. The biorthogonal wavelet order is specified by the order of these two filters.

5.2 Biorthogonal Wavelet: Bior 4.4

Biorthogonal 4.4 (Bior 4.4) is also known as Cohen Daubechies feauveau (CDF9/7) wavelet. The biorthogonal wavelet contains 9 coefficients in low pass filter bank and 7 coefficients in high pass filter bank in the analysis. Bior 4.4 wavelet has 4 vanishing moments. The structure of the wavelet is shown in Figure 5 and the filter coefficients are shown in Table 2.

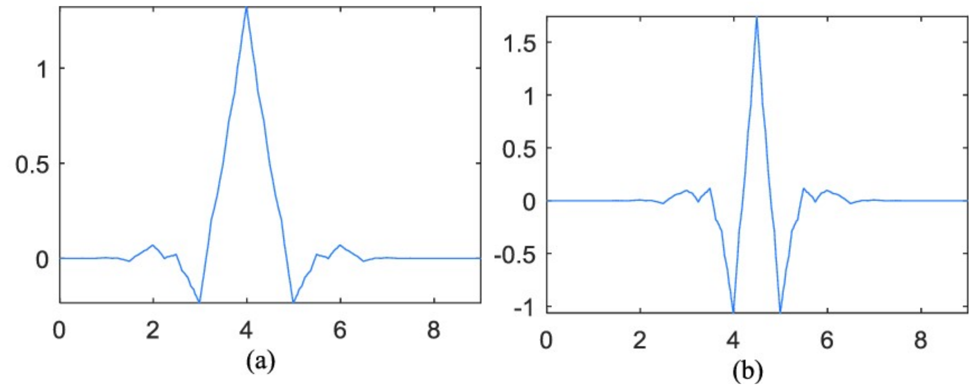

Fig. 5 Functions of biorthogonal 4.4: (a) scaling function; (b) wavelet function

Table 6: Filter coefficients for Bior4.4 wavelet

	Analysis		Synthesis	
n	Low pass filter	High pass filter	Low pass filter	High pass filter
0	+0.602949018236360	+1.115087052457000	+1.115087052457000	+0.602949018236360
±1	+0.266864118442875	-0.591271763114250	+0.591271763114250	-0.266864118442875
±2	-0.078223266528990	-0.057543526228500	-0.057543526228500	-0.078223266528990
±3	-0.016864118442875	+0.091271763114250	+0.091271763114250	+0.016864118442875
±4	+0.026748757410810			+0.026748757410810

6. Methodology

Part 1: Transformation

DWT is applied to the image for different levels. A trail is first done to determine which combinations give better compression results comparing CR to MSE and PSNR values. Finally, the best method proves to be images transformed with Bior4.4 wavelet in the initial levels and Haar wavelet in the remaining levels.

Part 2: Compression algorithm

SPIHT compression is applied to get the compression bit stream after transformation is complete. SPIHT algorithm is a progressive coding in which coding can be stopped when the target bit rate is achieved. SPIHT is in place coding scheme that produces a binary stream of compressed data straightaway [19]. SPIHT encoding is done using sorting and refinement pass. A variable $n = \lfloor \log 2(\max(i,j)\{|ci,j|\}\rfloor$ is used to control the algorithm flow. n is decremented after completing both sorting and refinement pass. In each sorting pass, the coefficient is selected such that $2n \leq |c(i,j)| < 2n + 1$. For n, if $|c(i,j)| \geq 2n$ then the coefficient is significant; otherwise insignificant. The most significant bit (MSB) of coefficients with the magnitude greater than the threshold in previous sorting passes is the output of refinement pass. Refinement pass output starts only from 2nd pass.

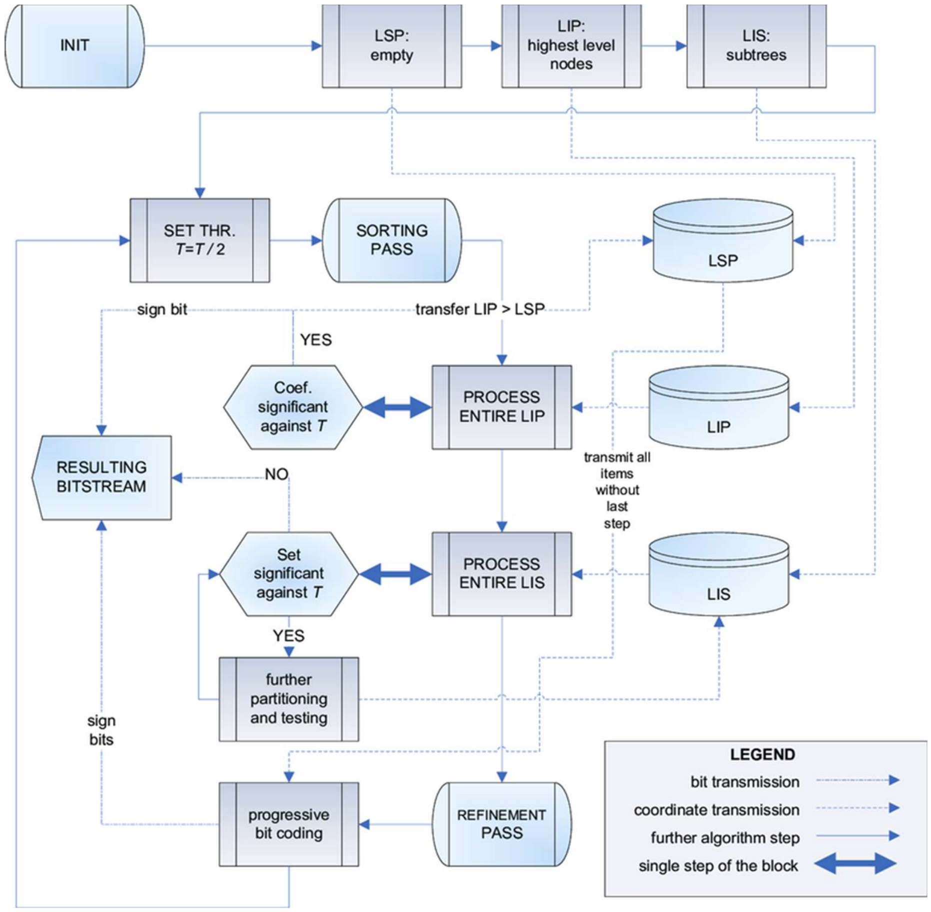

Fig. 6 Sorting pass: SPIHT Algorithm Scheme [17]

The algorithm flow of SPIHT is given below]:

1) Initialization: output $n = \lfloor \log'2 (\max(i,j)\{|c(i,j)|\}) \rfloor$; Set the LSP as an empty list, and add the coordinates (i, j)∈ H to the LIP, and only those with descendants also to the LIS, as type A entries.

2) Sorting Pass: Sorting pass code flow is shown in the figure above

3) Refinement Pass: for each entry (i, j) in the LSP, except those included in the last sorting pass (i.e., with same n), output the nth most significant bit of $|c_{i,j}|$;

4) Quantization-Step Update: decrement n by 1 and go to Step 2.

Sn is the compressed bitstream of the image. The LSP, LIP, and LIS are used only to generate the Sn and they are not part of the compressed data. The same algorithm used to reconstruct the coefficients except the term output in the algorithm must be replaced by input.

Evaluation Criteria

Peak signal to noise ratio (PSNR), mean square error (MSE), and compression ratio (CR) provide the compression performance metric.

Compression ratio is the ratio of nonzero elements in the original matrix to those in the updated converted matrix. The compression ratio, which is used to quantify the reduction in picture representation size brought about by a compression algorithm, is the ratio of the size of the compressed signal to the original signal. Higher compression ratios can result in worse-quality images even while lower compression ratios might yield higher-quality images.

$$Compression\ Ratio = \frac{Original\ Data\ Size}{Compressed\ Data\ Size} \tag{3}$$

While PSNR shows a measurement of the peak error, MSE shows the cumulative squared error between the compressed and original image. The error decreases as the MSE value decreases. Mean squared error is essentially a measurement of signal fidelity. A signal fidelity measure compares two signals by providing a numerical score that represents the degree of resemblance, fidelity, or error-distortion. However, it usually assumes that one signal is an error-free original and the other is warped or polluted.

$$SE = \frac{1}{mn}\sum_{y=1}^{m}\sum_{x=1}^{n}(I(x,y) - I^{1}(\boldsymbol{x},y))^{2} \tag{4}$$

where I is original image, $I1$ is approximation of decompressed image and m, n are dimensions of the image.

PSNR: The ratio of a signal's maximum potential power to the power of distorting noise that degrades the signal's representation quality. Because the signals have a very wide dynamic range, the PSNR is typically calculated as the logarithm term of the decibel scale when comparing two images. This ratio is computed in decibel form. This dynamic range fluctuates according to their quality, ranging from the greatest to the smallest possible values. It determines the ratio of the highest signal power that can be achieved to the noise that distorts the image and lowers the quality of the representation. The most popular method of evaluating quality that is used to gauge the quality of reconstruction of lossy image compression codecs is the peak signal-to-noise ratio. The noise is the error yielded by compression or distortion, and the signal is thought of as the original data. In comparison to compression codecs, the PSNR approximates how a human would perceive the quality of the reconstruction.

The PSNR for gray scale image (8 bits/pixel) is defined by-

$$PSNR(dB) = 20 \times \log_{10}(\frac{255}{\sqrt{MSE}}) \tag{5}$$

7. Results and Discussion

This section displays the outcome of applying compression on fingerprint images. The Sokoto Coventry Fingerprint Dataset (SOCOFing) test pictures were used. It is a biometric fingerprint database created for use in scholarly investigations. Six thousand fingerprint photos, separated into three categories, represent SOCOFing. For this study, the 'real' fingerprint category was used, and the photos were chosen at random. There are two sections to the experiment. Python Jupyter notebook was used to conduct the experiments.

7.1 Part one of the experiment

The number of levels of wavelet transformation are fixed and vary the Bior4.4 and Haar wavelet levels to match the total number of levels.

Table 7: Haar & Bior 4.4 out of 5 Levels: CR vs MSE & PSNR

Haar & Bior 4.4 = 5 levels				
HAAR	**BIOR4.4**	**CR**	**MSE**	**PSNR(dB)**
0	5	10.06	**32.725**	**30.724**
1	4	10.617	38.46	29.461
2	3	10.581	40.49	29.200
3	2	10.589	42.421	29.107
4	1	**10.6205**	42.48	29.140
5	0	10.604	42.003	29.140

Table 8: Bior 4.4 & Haar out of 5 Levels: CR vs MSE & PSNR

Bior 4.4 & Haar = 5 levels				
BIOR4.4	**HAAR**	**CR**	**MSE**	**PSNR(dB)**
0	5	10.604	42.0037	29.1404
1	4	10.62	35.76	30.159
2	3	10.585	32.754	30.485
3	2	10.594	**30.431**	**31.56**
4	1	**10.621**	30.58	31.556
5	0	10.06	32.7251	30.7242

Table 3 shows the values of MSE and PSNR with Haar wavelet in initial levels and Bior4.4 in remaining levels. Table 4 shows the values of MSE and PSNR with Bior4.4 in initial levels and Haar in remaining levels. It is evident that in Table 3; Haar at higher levels gives high compression however; the MSE & PSNR values are not the best for compression quality at that same level. The best MSE & PSNR results are given by level 5 Bior alone in table 3. This ascertains Gangwar's [13] point that Haar transformation alone gives excellent compression ratios but when it comes to preserving significant fingerprint information; it falls below international compression standard (this is shown by the MSE & PSNR values).

In table 3 the best compression results are presented by level 5 bior4.4 wavelet transform only (MSE:32.725; PSNR: 30.724). Observe that the very results become subpar in table 4 once the bior4.4 wavelet becomes the initial wavelet and haar is used at the remaining levels. Since good MSE results are given by the lowest MSE value and PSNR is given by the highest value; notice that table 4 has an improved set of results. Observing the results in Table 3 and Table 4; it is evident that Table 4 shows better results and there is a large deviation. Thus, the experiment is carried with Bior4.4 for initial levels and Haar in later levels. The values of MSE and PSNR are measured by keeping the compression ratio constant. It is clear that compression ratio alone cannot be depended on. Haar proves to really be good at extreme compression however; the important information is not preserved.

Below is the comparison of results from Table 4 and Table 5. The studied values are the MSE and PSNR versus CR for total levels 5 and 7.

Table 4: Bior 4.4 & Haar out of 5 Levels: CR vs MSE & PSNR

Bior 4.4 & Haar = 5 levels				
BIOR4.4	**HAAR**	**CR**	**MSE**	**PSNR(dB)**
0	5	10.604	42.0037	29.1404
1	4	10.62	35.76	30.159
2	3	10.585	32.754	30.485
3	2	10.594	**30.431**	**31.56**
4	1	10.621	**30.58**	**31.556**
5	0	10.06	**32.7251**	**30.7242**

Vs

Table 5: Bior 4.4 & Haar out of 7 Levels: CR vs MSE & PSNR

Bior 4.4 & Haar = 7 levels				
BIOR4.4	**HAAR**	**CR**	**MSE**	**PSNR (dB)**
0	7	10.4824	46.111	30.3083
1	6	10.489	34.827	31.588
2	5	11.4824	32.374	31.77
3	4	11.4858	**31.9854**	**31.9476**
4	3	11.4858	**32.1606**	**31.9246**
5	2	11.4858	**32.18**	**31.924**
6	1	10.4814	**32.339**	**31.922**
7	0	10.4824	**32.339**	**31.9012**

It is observed that irrespective of the number of total levels, a combination of Bior4.4 wavelet for initial 3 levels + remaining levels with Haar wavelet provides improved results. At this combination the observed value for MSE is minimum and the PSNR is maximum. This combination will be further used in part two of the experiment.

7.2 Part two of the experiment

Different images were tested using the better case from the first part. The total number of levels are 5 with the initial 3 levels being transformed using the Bior4.4 wavelet. Thus, the remaining 2 levels are transformed using Haar wavelet. A comparison is made between the proposed method and the transformation with only Bior4.4. An image is selected at random and the reconstructed image with Bior4.4 compression is shown in fig. 8 and the reconstructed image with the proposed method is shown in fig. 9 respectively.

Fig. 7 Original Fingerprint

Fig. 8 Bior4.4 Compressed

Fig. 9 Proposed Compression

Table 7 and Table 8 below show the measured values of MSE and PSNR of different fingerprint images. At this combination the observed value for MSE is minimum and the PSNR is maximum.

Table 6: CR vs MSE & PSNR of a Fingerprint Image

BIOR 4.4 Wavelet Only & SPIHT Compression		
CR	MSE	PSNR(dB)
1.930	0.554	50.551
3.000733	1.6335	46.6303
4.50419	5.23917	40.9542
6.00327	10.71227	37.73156
8.004864	20.19347	35.07964
10.0024	31.56249	33.1388
13.00317	50.43817	32.00154

Table 7: CR vs MSE & PSNR of a Fingerprint

Proposed Method: Bior4.4 & Haar Wavelet & SPIHT		
CR	MSE	PSNR(dB)
1.939	0.5146	50.567
3.002473	1.6232	46.66597
4.50971	5.17917	40.8818
6.009272	10.6121	37.77312
8.00681	19.7579	35.1532
10.0034	31.3725	33.1932
13.00327	49.4834	32.01124

The values obtained for various MSE and PSNR against compression ratios show that the proposed method provides better compression. Haar is a wavelet that cannot recognize abrupt changes and is not preferred for better compression results. But it provides better results when low frequency contents are more in the image. Since the bior4.4 wavelet removes major high frequency contents of the image, after 3 levels of transformation LL sub band contains low frequency contents in the majority. The feature proposed provides better performance.

8. Conclusion

The SPIHT technique is used in this work to compress fingerprint images after they have been transformed using various levels of the Haar and bior4.4 wavelet for discrete wavelet transform. The second portion of the experiment employed the same transformation technique-Bior4.4 wavelet because its application in the early stages of transformation produced superior MSE and PSNR values. The MSE and PSNR analysis at constant compression ratio shows bior4.4 for the first three transformation levels, and improved results are obtained by Haar for the remaining transformation levels. The contents of LL sub-band are low frequency since Bior4.4 separates high frequency items in the first stages of dyadic partition. The simplest wavelet, Haar, is effective at processing the image's low-frequency contents. When compared to using the Bior4.4 transformation alone, performance was improved by using the Bior4.4 for the first three levels and the Haar wavelet for the remaining levels. With the suggested strategy, the observed MSE and PSNR values for fingerprint compression is better. The incorporation of Convolutional Neural Network (CNN) techniques for fingerprint image compression may be covered in future articles, with an emphasis on how these techniques might improve compression effectiveness and image quality compared to using SPIHT Compression. Furthermore, investigating how well CNN architectures adapt to fingerprint image data after multiple wavelets at different levels of compression respond; this could pave the way for more specialized and efficient compression techniques in the field.

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References

[1] Reena Garg, Gunjan Singh, Aditya Singh , Manu Pratap Singh , Fingerprint Recognition using Convolution Neural Network with Inversion and Augmented Techniques, Soft Computing Letters (2024), https://doi.org/10.1016/j.sasc.2024.200106

[2] B. A. Lungisani, C. K. Lebekwe, A. M. Zungeru and A. Yahya, "Image Compression Techniques in Wireless Sensor Networks: A Survey and Comparison," in IEEE Access, vol. 10, pp. 82511-82530, 2022, doi: 10.1109/ACCESS.2022.3195891.

[3] Kamrul Hasan Talukder and Harada, K. (2010). Haar Wavelet Based Approach for Image Compression and Quality Assessment of Compressed Image.

[4] Emmanuel, Babatunde & Mu'Azu, Mb & Sani, Suleiman & Garba, Suleiman. (2014). A Review of Wavelet-Based Image Processing Methods for Fingerprint Compression in Biometric Application. British Journal of Mathematics & Computer Science. 4. 2781-2798. 10.9734/BJMCS/2014/11944.

[5] Goyal, V., Saxena, R., Chaudhary, A., Bhatt, S. C., & Uniyal, M. (2023). The Application of Discrete Wavelet Transform In Medical Image Compression. *J. Mountain Res.*, *18(1)*(P-ISSN: 0974-3030; E-ISSN: 2582-5011), 257–265.

[6] Kumar, D. & K B, Raja & Chhotaray, R. & Pattanaik, Sabyasachi. (2011). DWT Based Fingerprint Recognition using Non Minutiae Features. CoRR. abs/1106.3517.

[7] Kambli, Mansi & Bhatia, Shalini. (2010). Comparison of different Fingerprint Compression Techniques. An International Journal(SIPIJ. 1. 10.5121/sipij.2010.1103.

[8] Pal, H. S., Kumar, A., Vishwakarma, A., Singh, G. K., & Lee, H. (2024). A new automated compression technique for 2D electrocardiogram signals using discrete wavelet transform. *Engineering Applications of Artificial Intelligence*, *133*, 108123. https://doi.org/10.1016/j.engappai.2024.108123

[9] Ravichandran D, Nimmatoori Ramesh, Ashwin Diwakar MR Ashwin (2016) Medical Image Compression Based on Daubechies Wavelet, Global Thresholding and Huffman Encoding Algorithm. IJACECT. 5(1): 7-12.

[10] Sudhakar R, Jayaraman S. Fingerprint compression using multiwavelets. International Journal of Information and Communication Engineering. 2006;2:2.

[11] Kumar C, Shekhar C, Das S, Bhandari S. Compression algorithm by using wavelets. International Journal of Engineering Science and Technology. 2010;2(10):4978-4982.

[12] Mushen Z, Dababneh M, Al Nsour A. Wavelet and optimal re-quantization methodology for lossy fingerprint compression. International Arab Journal of Information Technology. 2011;8(4):383-387.

[13] Gangwar DK. Compression and development analysis on an image using Haar wavelet transform. IJATER. 2012;2(3):225-229

[14] Mohindru, Pankaj & Pooja, (2022). Comparative Analysis of Haar, Daubechies and Bior wavelets on Image Compression using Discrete Wavelet Transform.

[15] Anilkumar Katharotiya, Patel, S.J. and Mahesh Goyani (2011). Comparative Analysis between DCT & DWT Techniques of Image Compression. *Journal of Information Engineering and Applications*, 1(2), pp.9–17

[16] Alshareefi, Dr-Nidhal. (2013). Image compression using wavelet transform. Journal of Babylon University/Pure and Applied Sciences. 21. 1181-1190.

[17] Altameem. T, Alfarraj O, Zanaty E A, Tolba A and Ibrahim S M 2016 Performance analysis of medical image compression using various wavelet techniques J. Med. Imaging Heal. Informatics 6 1451–61

[18] Kumar, Ratesh. (2018). Historical Development in Haar Wavelets and Their Application - An Overview

[19] Malý, J & Rajmic, Pavel. DWT-SPIHT IMAGE CODEC IMPLEMENTATION.

[20] Prakash S Narayana and A M Khan 2020 J. Phys.: Conf. Ser. 1427 012002

[21] Stanković, R. S., & Falkowski, B. (2003a). The Haar wavelet transform: its status and achievements. *Computers & Electrical Engineering*, *29*(1), 25–44. https://doi.org/10.1016/s0045-7906(01)00011-8

[22] Abbas. A. W, Khan. W. U, Marwat S. N. K, Ahmed. S, Saeed. K, Arfeen. N, “Image Compression Exploration using Discrete Wavelets Transform Families and Level”, IJIST, Vol.6 Issue. 2 pp 366-379, April 2024