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To Determine the Best Wavelet by the Compression of an Image (Fingerprint) Using two Types of Wavelets Base on Wavelet and wavelet-packet

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ABSTRACT

Image compression has become a necessary step for making better use of available storage requirements and transmission bandwidth during the past decades. For image compression it is desirable that the selection of transform should reduce the size of resultant data set as compared to source data set. For continuous and discrete time cases, wavelet transforms and wavelet packet transform has emerged as popular techniques. This thesis paper aims to determine the best wavelet to compress the still image (fingerprint) at a particular decomposition level using wavelet transforms and wavelet packet transforms. Number of Zeros (NZ) and Retain Energy (RE) is determined for different wavelets at different threshold values ranging from 10 to 100 for decomposition level 3.

Introduction

Image Processing is one of the major applications where the compression will take crucial part in fingerprint, which is used for the application in scientific especially medical, knowledge legal matters as in the investigation of crime etc. In Crime sector fingerprint identification is one of the most reliable personal identification methods and it plays vital role. Since from 1924 to today, the US Federal Bureau of Investigation (FBI) has collected about 30 million sets of fingerprints [1].The big problem is the storage of data capacity. I. Daubechies in the field of orthonormal supported wavelet transformation; they started to think about electronic storage of fingerprint. Fingerprint images are digitized at a resolution of 500 pixels per inch with 256 levels of gray scale information per pixel. A single fingerprint is contained about 700,000 pixels and needs about 0.6 Mbytes to store. So digitizing the FBI's current achieved would result in about 200 Terabytes of data and prices of about $900 per Giga byte for hard disk storage, the cost of storing these uncompressed images would be about 200 million dollars. Obviously, data compression is necessary to bring these numbers down. there are many image compression techniques are already exists like DCT, JPGE, and JPGE2000 [2] and Wavelet etc all these techniques having their common aim to achieve high compression ratio. Among existing compression techniques wavelets gives better result for lossless image compression. But there is still need to develop faster, more strong and healthy algorithms for fingerprints and one of the main difficulties in developing the minutiae i.e. rides endings and bifurcations, which are subsequently used in identifications. Wavelet packets are used to achieve high compression ratios while retains these fine details and it also saves computational effort, transmission, and storage costs etc. The practical implementation of wavelet compression schemes is very similar to that of sub band coding schemes. As is case sub band coding, we decompose the signal (analysis) using filter banks. The outputs of the filter banks are dawn sampled, and recompose the signal [3], [4]. Wavelet analysis can be used to divide the information of an image into approximation and detail sub signals shows the vertical, horizontal and diagonal details or changes in the images. If these details are very small then they can be set to zero without significantly zero knows as threshold. The greater the number of zeros the greater the compression ratio. The amount of information retained by an image after compression and decompression is known as the retained energy and this is proportional to the sum of square of the pixel values. If the energy retained 100% then the compression is known as lossless as the image can be reconstructed exactly. This occurs when the threshold value is set to zero, meaning that the detail has not been changed. Ideally, during compression the number of zeros are obtained more energy retention will be as high as possible. However, as more zeros are obtained more energy lost, so a balance between the two needs to be found [5], [6].In addition to the above properties of wavelet transform, wavelet packets provide more flexible decompression at any node of the decomposition by allowing decomposition at any node of the decomposition tree and also to obtain the best decomposition tree [7]. The benefit of the wavelet packets over the wavelet decomposition comes from the ability of the wavelet packets to better represent high frequency (this is how image may contains a noise) content, and high frequency oscillating signals in particular, This allows wavelet packet to perform significantly better than wavelets for compression of images with large amount texture(like fingerprint images) and it is also point out the perceived image quality is significantly improved using wavelet packets instead of wavelets especially in the textured regions of the images [8].The filter design associated with the wavelet analysis method involves iterating the low-pass and high-pass filtering and down sampling procedure only on the low-pass branch of the previous. While, wavelet packet (WP) presenting on extension of the octave band wavelet decomposition to full tree decomposition i.e. the high pass output of each branch is also filtered and down sampled up to maximum no. of decomposition this is one of the key difference between the wavelet and wavelet packet. This paper presents the result of image compression for different mother wavelets. It is concluded that selection of proper mother wavelet is one of the important parameters of image compression. We propose mother wavelet db1 to db5, and, coif1 to coif5 for image compression.

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This selection is based on nature of the image. For fingerprint image compression different types of wavelet can be used and in this paper we have used family of Daubechies and Coiflet-type wavelets. We have analyzed Daubechies and Coiflets wavelet family to find most useful wavelet for fingerprint image compression by using wavelet and wavelet packet transform where, most useful wavelet has been chosen based on retain energy (RE) and number of zeros (NZ). According to this, to find most useful member from Daubechies and Coiflet's wavelet family our paper have made an experiment on this family by compression a fingerprint image. In this paper wavelet and wavelet packet transform have been used and most useful Coiflet-type wavelet has been chosen based on retain energy (RE) and number of zeros (NZ).In future if you want to use all member of Daubechies and Coflet's wavelet family then it would be better to use that most useful member to obtain better compression.

Wavelets

Wavelets are functions that are confined in finite domains and are used to represent data or a function. In an analogous way to wavelet analysis analyzes the scale of a function's content with special basis functions called wavelets. The wavelet means small waves and in brief, a wavelet is an oscillation that decays quickly. Equivalent mathematical conditions for wavelet are:

$$i)\ \int_R |\psi(x)|^2 dx < \infty$$

$$ii)\ \int_R \psi(x) dx = 0$$

$$iii)\ \int_R \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty$$

where $\hat{\psi}(\omega)$ is the Fourier Transform of $\psi(x)$.

Discrete Wavelet Transform:

The wavelet transform is first introduced for the time-frequency analysis of transient continuous signal, and then extended to the theory of multi-resolution wavelet transform using filter approximation. The discrete wavelet $\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n)$ used in multi-resolution analysis constituting an orthonormal basis for $L^2(\Re)$. $x(t)$ is decomposition an different scale

$$x(t) = \sum_{m=1}^{L}[\sum_{k=-\alpha}^{\alpha} D_m(k)\psi_{m,k}(t) + \sum_{k=-\alpha}^{\alpha} A_L(k)\phi_{L,k}(t)]$$

where $\psi_{m,k}(t)$ is discrete analysis wavelet, and $\phi_{L,k}(t)$ is discrete scaling, $D_m(k)$ is the detailed signal at 2^L. $D_m(k)$ and $A_L(k)$ is obtained using the scaling and wavelet filters.

$$h(n) = 2^{-1/2}\langle\phi(t), \phi(2t-n)\rangle$$
$$g(n) = 2^{-1/2}\langle\psi(t), \phi(2t-n)\rangle = (-1)^n h(1-n)$$

Again the concept of discrete wavelet transform is shown in Fig. 1.

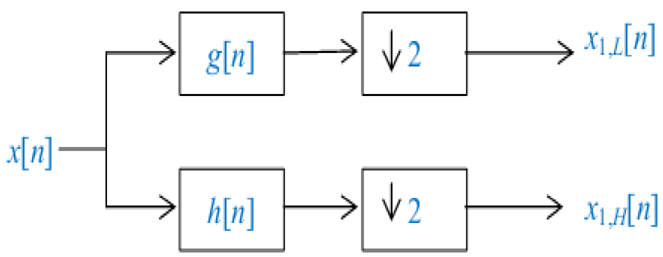


Fig 1. The concept of discrete wavelet transforms

Where $x[n]$ is the input, $h[n]]$ is the high pass filter, $g[n]]$ is the low pass filter, and $\downarrow 2$ is the down-sampling by the factor of 2, $x_{1,L}[n]$ is the output of the low pass filter, and $x_{1,H}[n]$ is the output of the high pass filter. Where $g[n]$ is just like the mother wavelet function in continuous wavelet transform, and $h[n]$ is the just like the scaling function in continuous wavelet transform. The coefficients of Daubechies filters are usually used for $h[n]$ and $g[n]$. $x_{1,L}[n]$ is the rough part of the input $x[n]$ and $x_{1,H}[n]$ is the detail part of input. In image compression, we usually keep $x_{1,L}[n]$ and discard $x_{1,H}[n]$ to achieve the compression

2D Wavelet Transform

2D wavelet transform is shown in Fig. 2.2D wavelet transform is the combination of two 1D wavelet transform. First we do the 1D wavelet transform along n, and then do the 1D wavelet transform along m.

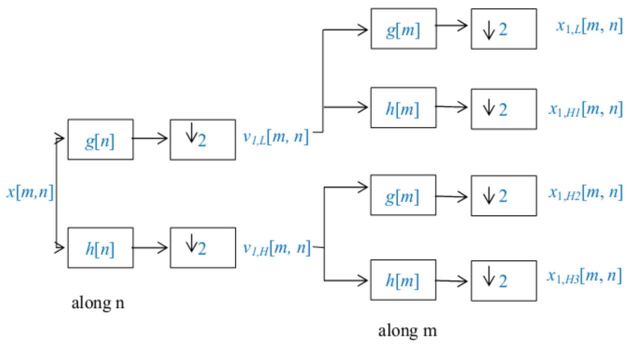


Fig 2. The concept of 2D discrete wavelet transforms

When we use the 2D discrete wavelet transform in an image, we will obtain 4 part of output, which the size of each part is one fourth of the original size. Fig. 3 is the output of Sundarban processed by 2D discrete wavelet transform.

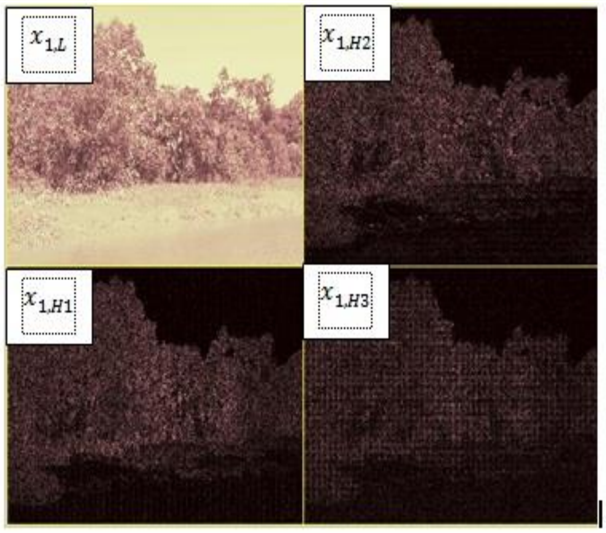


Fig 3. Sundarban processed by 2D discrete wavelet transform

We can see that the $x_{1,L}$ is just like the original image, and the $x_{1,H1}$, $x_{1,H2}$, $x_{1,H3}$ are respective corresponding to the horizontal edges, vertical edges, and corners. We can use the characteristic to do image compression

Wavelet packets:

We know that orthonormal wavelet bases have a frequency localization which is proportional to 2^j at the resolution level j. The wavelet bases have poor frequency localization when j is large. The wavelet packet method is a generalization of wavelet decomposition that offers a richer signal and image analysis. Wavelet packet atoms are waveforms indexed by three naturally interpreted parameters: position, scale (as in wavelet decomposition), and frequency. For a given orthogonal wavelet function, we generate a library of bases called wavelet packet bases. Each of these bases offers a particular way of coding signals, preserving global energy, and reconstructing exact features. The wavelet packets can be used for numerous expansions of a given signal [9]. There exist simple and efficient algorithms for both wavelet packet decomposition and optimal decomposition selection. We can then produce adaptive filtering algorithms with direct applications in optimal signal coding and data compression. In wavelet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level approximation and detail, and the process is repeated. For $n-1$ level decomposition, there are $n+1$ possible ways to decompose or encode the signal

Wavelet and Wavelet Packet Transformation:

Wavelet Theory deals with both discrete and continuous cases. Continuous wavelet transform (CWT) is used in the analysis of sinusoidal time varying signals [3]. CWT is difficult to implement and the information that has been picked up may overlap and results in redundancy. If the scales and translations are based on the power of two, DWT is used in the analysis. It is more efficient and has the advantage of extracting non overlapping information about the signal. 2-D transform can be obtained by performing two 1-D transform. Signal is passed through low pass and high pass filters L & H, then decimated by a factor of 2, consisting 1 level transform, thus splitting the image into four sub-bands referred as LL, HL, LH & HH (Approximation, Horizontal Detail, Vertical Detail, and Diagonal Detail respectively). Further decomposition is achieved by acting upon four sub-bands. The inverse transform is obtained by up sampling all the four sub-bands by a factor of 2 and then using reconstruction filter. Higher scales correspond to more stretched wavelet.

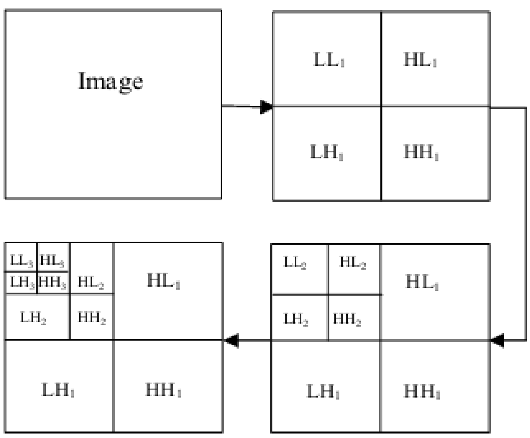


Fig 4. Three levels Wavelet Decomposition applied on an image

DWT, being non-redundant is a powerful tool for many non stationary processing applications but suffer from major limitations: poor directionality, absence of phase information, aliasing is some of them. The wavelet packet method is a generalization of wavelet decomposition that offers better representation of high frequency information. In wavelet transformation, the approximation component of image is further decomposed for next level decomposition whereas in wavelet packet transformation, approximation as well as detailed components is decomposed. The structure of two level decomposition of wavelet packet is shown in Fig. 5. Wavelet packet atoms are indexed by 3 parameters: position, scale & frequency.

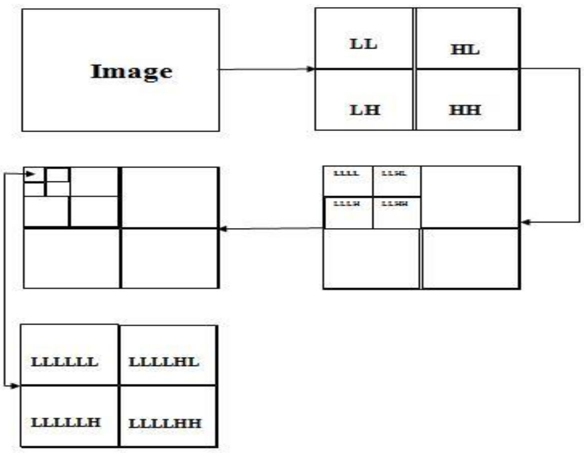


Fig 5. Three level wavelet packet decomposition on an image

Implementation

Image compression procedure contains decomposition, thresholding followed by reconstruction of the test image. In wavelet packet decomposition, for the chosen entropy optimal wavelet packet tree is computed before thresholding. The implementation steps for image compression thus involves following steps:

1. Decompose: Choose a wavelet and compute wavelet decomposition at level N.
2. Computation of tree: For the given entropy, compute optimal wavelet packet tree.
3. Threshold: Select Threshold value at each level from 1 to N.
4. Reconstruct: Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of level 1 to N.

The original standard indexed image of Barbara with 256 X 256 pixels is used as the test image. From the simulations Performance parameter RE and NZ with respect to different threshold (THR) values are obtained for all members of different wavelets family at decomposition level 3 using DWT and DWPT. The competing members are selected for comparison.

Image Compression Methodology:

There are various methods of compressing still images, but every method has three basic steps involved in any of the data compression scheme: Transformation, reduced precision (quantization or thresholding), and minimization of number of bits to represent the image (encoding). The basic block diagram of compression scheme is shown in Fig. 6.

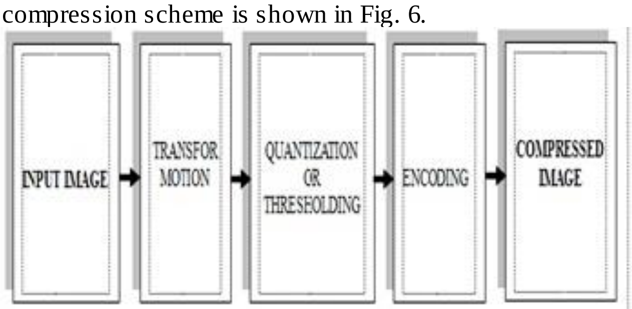


Fig 6. The block diagram of image compression scheme

Fingerprint image compression:

We have implemented the above discussed wavelet and wavelet packet algorithm between Daubechies's and Coiflet's wavelet for a fingerprint image compression. In our test we have used 8-bit gray scale digitized thumb digitized fingerprint image of size 256×256 in MATLAB program.

Fig 7. Thumb digitized fingerprint image

For all Daubechies and Coiflet-type wavelets we have used global thresholding at different thresholding values 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 at the decomposition level 3. Results are observed in terms of percentage of zeros, percentage of energy retained. The results are presented in tabular form for wavelet and wavelet packet transform respectively for having percentage of number of zeros (NZ) and percentage of energy retained (RE) as follows [10],

$$NZ = \frac{100*\left(ZCZ100\right)}{No0\ fcoefficients}$$

$$RE = \frac{100*\left(V_n\left(CCD,2\right)\right)^2}{\left(V_n\left(Originalsignal\right)\right)^2}$$

Where V_n is the vector norm, CCD is the coefficients of the current decomposition and ZCD is the Number of zeros of the current decomposition. In this test Shannon entropy criterion is used to construct the best tree. Shannon entropy criteria find the information content of signal "*S*".

Information content of decomposed component (approximation and details) may be greater than the information content of components, which has been decomposed. In this test the sum of information of decomposed component (child node) is checked with information of component which has been decomposed (parent node) and if sum of information of child nodes is less than the parent node, then only parent node is decomposed and child nodes are considered in tree otherwise parent nodes are not decomposed.

Wavelet and wavelet packet decomposition of the fingerprint image are shown in fig 8.

The thresholding of wavelet and wavelet packet coefficients is performed, if the value of the coefficients of the leaf node (except for the approximation) is less than threshold number then it becomes zero.

Compression at 3rd level:

After processing the image compression (finger print) at 3rd level using the various wavelets for wavelet and wavelet packet decomposition we get some compress numerical data. The following tables and corresponding figures represent Retained energy and Number of zero in mentioned noiseless fingerprint image after compression at 3rd level at ten distinct threshold values for wavelet and wavelet packet algorithm by using Daubecies and Coiflet wavelets. 1st one the flowing figures shows that Wavelet and wavelet packet decomposition at 3rd level has been show in fig. 8.1st one of the following figures has been compressed in wavelet also 2nd one has compressed in wavelet packet. We have seen that left side of both images of the top are like original image after compressing. But 2nd recovered image gives more Retain energy along with Number of zeros than 1st recovered image.

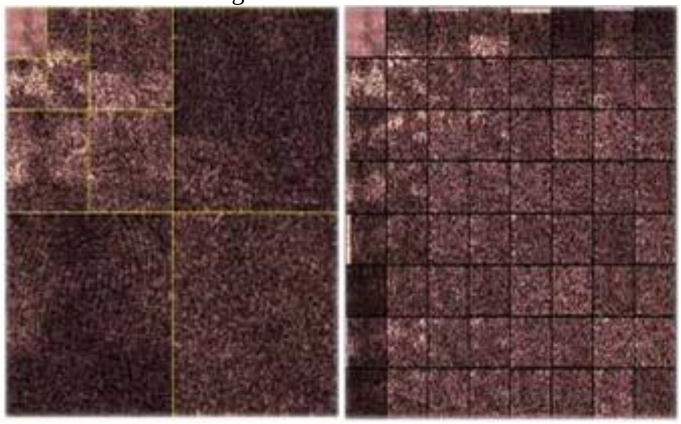


Fig 8. Wavelet and Wavelet packet Decomposition at level 3

Results and Discussion

The curves of THR vs RE for Competing members of Daubechies and Coiflet wavelet family have been calculated and depicted in figure from 9 to 14 for level 3. The curves are summarized in Table 5, where from it is concluded that at level 3 Wavelet transform: Though Wavelet Daubechies 5 gives highest RE than any other family of Daubechies family wavelet at different THR from 10 to 100 from fig. 9.Also we see that from fig. 11 Coiflet 5 gives higher RE than any other family of Coiflet family in Wavelet transform. Again we see that from fig. 10 and fig. 12 respectively Daubechies 5 and Coiflet 5 gives higher RE than any other family member of Daubechies and Coiflet wavelets in wavelet packet transform.

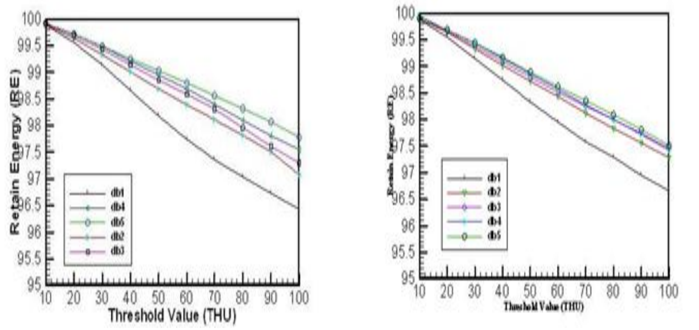


Fig 9 & 10. THU VS RE comparison of wavelet and wavelet packet transform at 3rd level fot table 1 and table 2 respectavely

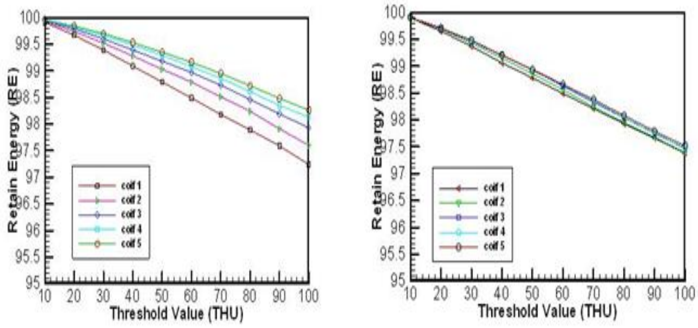


Fig 11&12. THU VS RE comparison of wavelet and wavelet packet transform at 3rd level for table 3 and table 4 respectively

Table 1. RE for wavelet transform at 3rd level for ten threshold values

		Retain Energy in (%) of different wavelets transform at different threshold value									
		Theshold value									
Wavelt functions	RE	10	20	30	40	50	60	70	80	90	100
Db 1	(%)	99.89	99.56	99.14	98.66	98.18	97.74	97.36	97.04	96.73	96.43
Db 2	(%)	99.90	99.64	99.33	99.01	98.69	98.39	98.4	97.82	97.51	97.18
Db 3	(%)	99.91	99.69	99.43	99.14	98.85	98.59	98.31	97.96	97.61	97.31
Db 4	(%)	99.92	99.72	99.48	99.21	98.95	98.69	98.40	98.10	97.81	97.55
Db 5	(%)	99.92	99.72	99.49	99.25	99.05	98.80	98.56	98.32	98.07	97.78

Table 2. RE for wavelet packet transform at 3rd level for ten threshold values

		Retain Energy in (%) of different wavelets packet transform at different threshold value									
		Theshold value									
Wavelt functions	RE	10	20	30	40	50	60	70	80	90	100
Db 1	(%)	99.88	99.55	99.15	98.74	98.33	97.95	97.58	97.29	96.95	96.66
Db 2	(%)	99.89	99.64	99.33	99.02	98.72	98.43	98.12	97.83	97.56	97.28
Db 3	(%)	99.90	99.66	99.38	99.09	98.80	98.51	98.25	98.00	97.74	97.46
Db 4	(%)	99.95	99.68	99.43	99.15	98.86	98.57	98.27	98.00	97.72	97.47
Db 5	(%)	99.90	99.69	99.44	99.17	98.89	98.62	98.35	98.09	97.81	97.51

Table 3. RE for wavelet transform at 3rd level for ten threshold values

		Retain Energy in (%) of different wavelets transform at different threshold value									
		Theshold value									
Wavelt functions	RE	10	20	30	40	50	60	70	80	90	100
Coif 1	(%)	99.91	99.67	99.39	99.09	98.79	98.49	98.18	97.89	97.59	97.24
Coif 2	(%)	99.93	99.74	99.52	99.28	99.03	98.79	98.51	98.24	97.91	97.60
Coif 3	(%)	99.94	99.79	99.60	99.39	99.18	98.97	98.73	98.46	98.19	97.93
Coif 4	(%)	99.95	99.82	99.66	99.48	99.29	99.08	98.86	98.61	98.35	98.13
Coif 5	(%)	99.96	99.84	99.70	99.53	99.35	99.16	98.95	98.72	98.48	98.26

Table 4. RE for wavelet packet transform at 3rd level for ten threshold values

		Retain Energy in (%) of different wavelets packet transform at different threshold value									
		Theshold value									
Wavelt functions	RE	10	20	30	40	50	60	70	80	90	100
Coif 1	(%)	99.90	99.65	99.37	99.06	98.78	98.49	98.21	97.93	97.66	97.38
Coif 2	(%)	99.90	99.69	99.43	99.15	98.86	98.56	98.24	97.95	97.68	97.39
Coif 3	(%)	99.91	99.70	99.46	99.20	98.93	98.63	98.33	98.04	97.75	97.47
Coif 4	(%)	99.91	99.71	99.47	99.21	98.94	98.65	98.36	98.05	97.76	97.48
Coif 5	(%)	99.91	99.71	99.48	99.21	98.94	98.66	98.38	98.08	97.79	97.52

Table 5. Comparison of Wavelet transform and Wavelet packet transform

Decomposition Level 3 Threshold Level	Wavelet Transform	Wavelet Packet Transform
Low THR Level	db 1,db 2, db 3,db 4 gives lowest RE consecutively db 5 gives highest RE coif 1,coif 2,coif 3,coif 4 gives lowest RE consecutively coif 5 gives highest RE	db 1,db 2, db 3,db 4 gives lowest RE consecutively db 5 gives highest RE coif 1,coif 2,coif 3,coif 4 gives lowest RE consecutively coif 5 gives highest RE
High THR Level	db 1,db 2, db 3,db 4 gives lowest RE consecutively db 5 gives highest RE coif 1,coif 2,coif 3,coif 4 gives lowest RE consecutively coif 5 gives highest RE	db 1,db 2, db 3,db 4 gives lowest RE consecutively db 5 gives highest RE coif 1,coif 2,coif 3,coif 4 gives lowest RE consecutively coif 5 gives highest RE

In compression of wavelet between db 5 and coif 5 from fig. 13 given higher RE we seen that the coif 5 gives higher RE than db 5 in wavelet transform, also coif 5 gives higher RE than db 5 in wavelet packet transform from fig. 14.

In this section we have discuss the effect of Daubechies and Coiflets-type on result through several graphs are drawn in various following figures. For Daubechies wavelet transform all figures showing us all RE are increasing at same threshold value for each different threshold values. Also we get the same result for Coiflet wavelets. For wavelet-packet transform all figure showing us RE are increasing with the increasing of Daubechies and Coiflets type wavelets order at same threshold value for each different threshold values and increasing rate is comparatively good. From both transformation we are observing that the higher orders Coiflets type gives much better compression result (i,e. more RE) than his lower orders Daubechies and oiflet's wavelets. From fig. 15 to 18 we see that for 10, 20, 30, 40, threshold values of Coiflets gives RE increasing but NZ are decreasing in wavelet transform. For wavelet-packet transform we see that these graphs as well as (RE) are increasing with NZ. Hence we would like to say that RE and NZ are increasing by increasing order of Coiflets wavelet than any other wavelets.

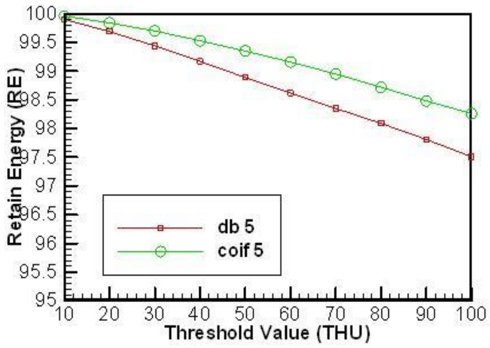


Fig 13. THU VS RE comparison for differet wavelet at 3rd level wavelet transform

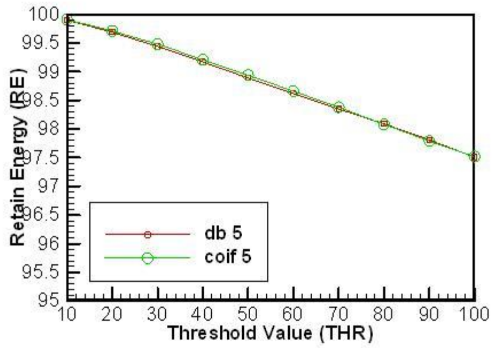
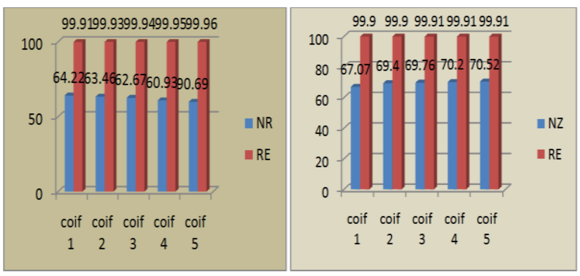
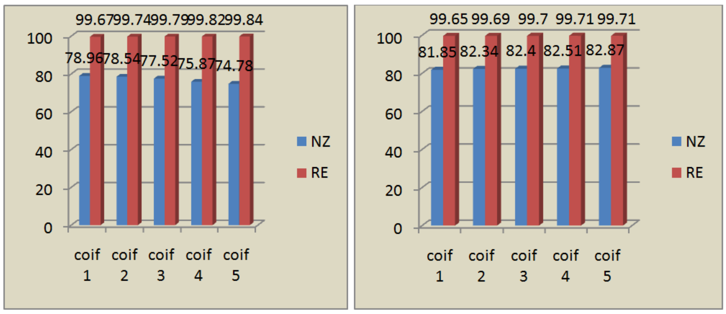


Fig 14. THU VS RE comparison for differet wavelet at 3rd level wavelet packet transform



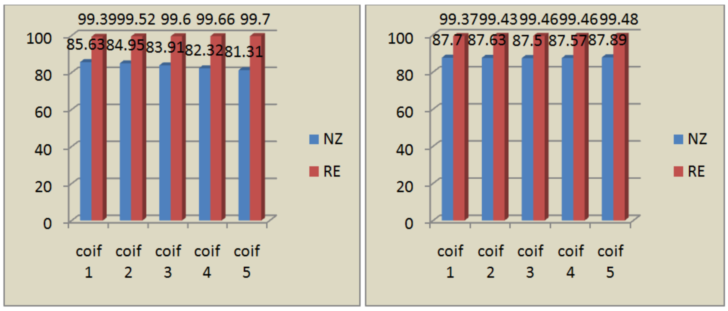
Threshold value 10

Fig 15. THU VS RE comparison of Coiflet at 3rd level decomposition



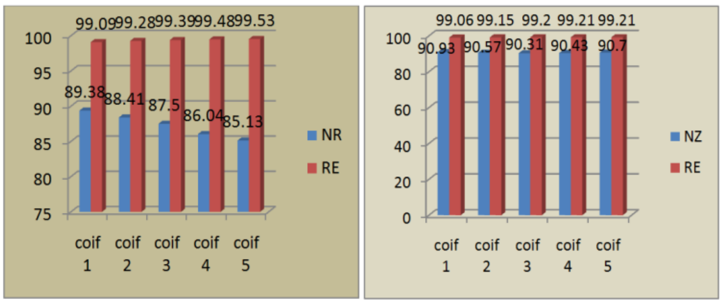
Threshold value 20

Fig 16. THU VS RE comparison of Coiflet at 3rd level decomposition



Threshold value 30

Fig 17. THU VS RE comparison of Coiflet at 3rd level decomposition



Threshold value 40

Fig 18. THU VS RE comparison of Coiflet at 3rd level decomposition

Conclusion

In this thesis we have analyzed every different Daubechies and Coiflet-type by compression a fingerprint image using wavelet and wavelet-packet transform at 10 different threshold values at 3rd decomposition level. For fingerprint image experiment result is that the Coiflet 5 is much better than other family members of Daubechies and Coiflet-type for wavelet transform and wavelet packet transform. In both case, we use the percentage of Retain Energy (RE) and percentage of Number of Zeros (NZ).In the case of wavelet transform percentage of Retain Energy (RE) is improved and percentage of Number of Zeros (NZ) is decreased. But in the case of wavelet packet transform the percentage of Retain Energy (RE) and percentage of Number of Zeros (NZ) both are improve at same threshold for each threshold values. Hence wavelet packets transform gives much better result than wavelet transform.

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