Fingerprint image de-noising using multi-resolution analysis (MRA) through stationary wavelet transform (SWT) method

Gornale S.S.[*], Humbe V.[#], Manza R.[#] and Kale K.V.[#]
[#]Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, (MS) - 431004 India
[*]Department of Computer Science, Government College(Autonomous), Mandya –Karanataka-India
shivanand_goranale@yahoo.*com*,vikashumbe@yahoo.co.in, ramesh_manza@yahoo.com

Abstract— almost every fingerprint image data contains noise. Noise reduction is a required step for any sophisticated algorithms in computer vision and image processing. This problem has existed for a long time and yet there is no good enough solution for it. A trade between the removed noise and the blurring in the image always exist. The most common methods used to acquire the fingerprint images do not need expertise, but highly distorted images are still possible because of dryness of skin, skin disease, dirt or humidity. Therefore such type of images must be de-noised for recognition. Many researchers have proved advantages of Discrete Wavelet Transform (DWT) for image de-nosing. DWT in image de-noising has limitations due to its non-invariance in time/space. The time invariant properties of un-decimated Discrete Wavelet Transforms are useful for de-noising the image. In this paper we have studied different thresholding methods. And the quality of de-noised image is evaluated through structural distortion measurement and also measured the computational processing time at each level. In our opinion this algorithm gives the best results in terms of visual quality less blurring for larger noise removal.

Keywords- Fingerprint Image, Un-decimated Wavelet Transform, Thresholding

I. Introduction

Biometric system is an imperative area of research in recent years. The biometric system having two important utility 1) authentication or verification of people's identity and 2) Identification in which persons identity is verify by biometric sign. The biometric systems consists different signs fingerprint, face, iris, hand, Pam etc. Out of these signs fingerprint is one of the oldest and most reliable sign used in identification systems [1,2]. In a recently published World Biometric Market Outlook (2005-2008), analysts predict that while the average annual growth rate of the global biometric market is more than 28%, by 2007. The technologies that would be included are fingerprint technology by 60%, facial & iris by 13%, keystroke by 0.5% and digital signature scans by 2.5% [3]. In fingerprint recognition system the de-noising of fingerprint image, feature extraction and matching are important features for identification. The de-noising is one of the great importances as it influences the performance of subsequent feature extraction and matching. The most common method use to acquire the fingerprint image is to obtain the impression by rolling an inked finger on paper and then scanning it using flat bed scanner. This method may result in highly distorted fingerprint images and thus it should be carried out by a trend professional. The live scan method provides better images and therefore it does not need expertise but highly distorted images are still possible because of dryness of skin, skin disease, sweat, dirt or humidity. The performance of fingerprint recognition system is depends on the quality of input fingerprint image. If the quality of input fingerprint is not good, automatic fingerprint identification or authentication is extremely difficult [4-8]. Therefore it is often needs to de-noise the fingerprint image. In this paper we have dealt both orthogonal and bi-orthogonal wavelet filters to de-noise the fingerprint image. And we have proposed new approach based on un-decimated wavelet transform theory to provide enhanced approach for eliminating such noise source and ensure the better identification. Many researchers have proved advantages of Discrete Wavelet Transform (DWT) for image de-nosing. DWT in image de-noising has limitations due to its non-invariance in time/space. The algorithm is based on the idea of no decimation. It applies the wavelet transform and omits both down-sampling in the forward and up sampling in the inverse transform. More precisely, it applies the transform at each point of the image and saves the detail coefficients and uses the low-frequency coefficients for the next level. The size of the coefficients array does not diminish from level to level this improves the

power of Stationary Wavelet Transform (SWT) in signal de-noising.
This paper is organized as follows the section-2 deals with DWT, SWT and its properties. Section-3 deals with wavelet thresholding. Section-4 deals with Image Quality evaluation. The Results and Discussion are discussed in Section-5 and Section-6 deals with conclusion followed by the reference.

II. Methodology

II.1 Discrete Wavelet Transform (DWT)

Basically image de-noising techniques are fall into two basic categories namely spatial domain and frequency domain. Wavelet Transform (WT) is one of the frequency domain techniques emerged as very powerful tool and provide a vehicle for digital image processing applications. Wavelets are applicable in medical research in 1991 for noise reduction [9]; due to its ability to take into account of Human Visual System (HVS) characteristics and good energy compaction capabilities under transmission and decoding. It is also more robust under transmission and decoding error. With standard DWT, signal has same data size in transform domain and therefore it is a non-redundant transform. Standard DWT can be implemented through simple filter bank structure of recursive FIR filters. One of the important property of DWT is Multi-resolution Analysis (MRA) allows DWT to view and process different signals at various resolution levels [10]. The advantage of non-redundancy over a Continuous Wavelet Transform (CWT) helps to implement fast and simple with a digital filter. The MRA capability populated with DWT in many signals and image processing applications from last two decade. Many researchers have successfully applied and proved the advantages of DWT for signal and image de-noising and also in compression in number of diverse fields [11, 12, 13, 14, 15, 16, 17]. As DWT is a powerful tool for signal and image processing applications; but it has three serious disadvantages. First is shift sensitive: because input signal shift generate unpredictable changes in DWT coefficients. Second it suffers from poor directionality: because DWT coefficients reveal only three spatial coefficients i.e. Diagonal (D), Horizontal (H) and Vertical (V). And the third is, it lacks the phase information that accurately describes non-stationary signal behavior. And the use of larger DWT basis function or wavelet filters produces blurring and ringing noise near edge regions image or video. These disadvantages severely restrict its scope for certain signal and image processing applications [18]. The Stationary Wavelet Transform (SWT) has overcome the non-invariance property of Discrete Wavelet Transform (DWT).

II.2 Wavelet Properties

The selection of wavelet filters plays a crucial part in achieving an effective de-noised image quality, because there is no filter that performs the best for all images [19, 20]. The choice of optimal wavelets has several criteria. And some of them are:

1. Filter Length
2. Smoothness
3. Filter magnitude response
4. Decomposition level

Wavelet Filter can be used to analyze or decompose signals and images called decomposition. The same components can be assembled back into the original signal without loss of information, which is called reconstruction or synthesis. Shorter synthesis basis functions are desirable for minimizing distortion that affects the subjective quality of the image. Longer filters are responsible for ringing noise in the reconstructed image at low bit rates. Each wavelet family is parameterized by an integer N called the filter order for example DbN, which is proportional to the length of the filter. The length of the filter is related to the degree of the smoothness of the wavelet and which is affect on image quality. This relation is different for different wavelet families and non-smoothness basis function introduces artificial discontinuities that are reflected as spurious artifacts in the reconstructed images. Higher filter order gives more energy and increases the complexity of calculating the DWT coefficients and these properties depends on the image contents. Filter Response is another critical property that affects the subjective quality of the reconstructed image. Another important factor is to consider the level of decomposition or the level of resolution. The first level is the finest or highest resolution and the final level is the coarsest or lower resolution. Any number of decomposition levels is considered to decompose the image. However, only level 1 to 8 is evaluated to avoid de-noising too much into coarsest levels. In, general if an optimal resolution level is used the best de-noising results can be obtained at level 5 [21, 22].

II.3 Overview of Stationary Wavelet Transform(SWT)

Wavelet Transform is superior approach to other time-frequency analysis tools like Fourier Transform (FT) and Short Term Fourier Transform (STFT) because its time scales width of the window can be restricted to match the original signal especially in image processing applications. This makes that it is particularly useful for non-stationary signal analysis such as noises and transients. For discrete signal, DWT is a Multi-resolution Analysis (MRA) and it is a non-redundant decomposition. The drawback of non-redundant transform is their non-variance in time [10]. The stationary wavelet transform (SWT) was introduced in 1996 to make the wavelet decomposition in time invariant [23, 24]. In order to preserve the invariance by translation, the downsampling operations must suppressed and the decomposition obtained is redundant and is called stationary wavelet transform, which is as shown in figure 1.

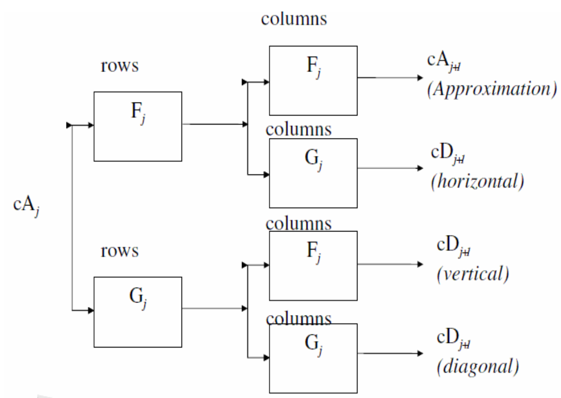

Figure 1: Stationary Wavelet Transform (SWT)

SWT has similar tree structured implementation without any sub-sampling. This balance of Perfect Reconstruction (PR) is preserved through level dependent zero padding interpolation of respective low pass and high pass filters in the filter bank structure. SWT has equal length of wavelet coefficients at each level. The computational complexity of SWT is high as compared to Discrete Wavelet Transform and need larger storage space. And which is represented as O (n^2). The redundant representation of SWT makes shift-invariant and suitable for applications such as edge detection, de-noising and data fusion [25, 26]. In stationary wavelet transform (SWT) instead of down sampling, an up sampling procedure is carried out before we separate the variables x and y of image f (x, y) shown in the following wavelets:

Vertical wavelet (LH): $\varphi^1(x,y) = \phi(x)\varphi(y)$

Horizontal Wavelet (HL): $\varphi^2(x,y) = \varphi(x)\phi(y)$

Diagonal Wavelet (HH): $\varphi^3(x,y) = \varphi(x)\varphi(y)$ …(1)

Where φ the wavelet is function and ϕ is the scaling function. The detailed signals contained in the three sub-images are as follows:

$$w^1_{j+1}(k_x,k_y) = \sum_{lx=-\infty}^{+\infty}\sum_{ly=-\infty}^{+\infty} g(lx)h(ly)c_{j,k+2^j}(lx,ly)$$ … (2)

$$w^2_{j+1}(k_x,k_y) = \sum_{lx=-\infty}^{+\infty}\sum_{ly=-\infty}^{+\infty} h(lx)g(ly)c_{j,k+2^j}(lx,ly)$$ … (3)

$$w^3_{j+1}(k_x,k_y) = \sum_{lx=-\infty}^{+\infty}\sum_{ly=-\infty}^{+\infty} g(lx)g(ly)c_{j,k+2^j}(lx,ly)$$ … (4)

III. Wavelet Thresholding

An image is often corrupted by a noise during acquisition and transmission. Image de-noising is used to remove the additive noise while retaining as much as possible the important features. There are various techniques available for de-noising the signals and images. Wavelet thresholding is an effective method of de-noising noisy signals; which plays an important role in de-noising the image and it is treated as widely investigated noise reduction method [14, 15, 27, 28, 29, 30]. The wavelet de-noising is achieved via thresholding. Wavelet thresholding procedure removes noise by thresholding only the wavelet coefficient of the details coefficients, by keeping the low-resolution coefficients unaltered. There are two thresholding methods frequently used: soft thresholding and hard thresholding.

III.1 Thresholding

The plot of wavelet coefficients suggests that small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information than noise. Replacing noisy coefficients (small coefficients below a certain threshold value) and an inverse wavelet transform may lead to a reconstruction that has lesser noise.

III.2 Hard and Soft Thresholding

Hard and soft thresholding with threshold ¸ are defined as follows:

The hard thresholding operator is defined as:

D (U, λ) = U for all |U|> λ

= 0 otherwise

The soft thresholding operator on the other hand is defined as:

D (U, λ) = sgn (U) max (0, |U| - λ)

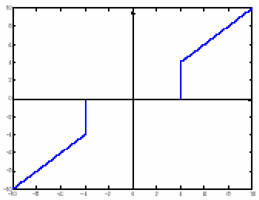

Figure-2 Hard Thresholding

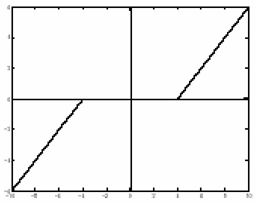

Figure-3 Soft Thresholding

Hard threshold is a "keep or kill" procedure and is more intuitively appealing. The transfer function of the same is shown in Figure-2. The alternative soft thresholding whose transfer function is shown in Figure-3, shrinks coefficients above the threshold in absolute value. While at first sight hard thresholding may seem to be natural, the continuity of soft thresholding has some advantages. It makes algorithms mathematically more tractable. Moreover, hard thresholding does not even work with some algorithms such as the GCV procedure. Sometimes, pure noise coefficients may pass the hard threshold and appear as annoying 'blips' in the output. Soft thresholding shrinks these false structures.

Wavelet Thresholding is an effective method of de-noising the noisy signals, which plays an important role in de-noising an image and is treated as widely investigated noise reduction method. The general procedure for de-noising through soft thresholding includes the following three steps.

- Decompose the image through Forward Wavelet Transform
- Threshold detail coefficients (i.e. Diagonal, Horizontal and Vertical)
- Reconstruct (Inverse Transform) using thresholded coefficients.

In the above three steps, firstly the image is decomposed by the wavelet transform, and then secondly the detail coefficients are thresholded. Various thresholding techniques based on wavelet domain-filtering techniques such as SUREthresh, Visuthresh and Bayesthresh, Hybridthresh, Invshrink, MinMaxThresh, MultiMAD, etc; among these Invshrink, SUREthresh are the safe choices for de-noising [31]. The SURE shrink thresholding algorithm [14] is used to threshold the detail coefficients. After the thresholding, the new detail coefficients are obtained; using these new coefficients the image is reconstructed, which is the de-noised image by wavelet transform [21,32,33,34].

IV. Image Quality Evulation

After de-noising the image, it is often necessary to measure the quality of the original and de-noised images. Therefore, quality measures play an important role in image processing applications. Basically two kinds of quality measures are used to measure the quality of the images: Objective quality measures and Subjective quality measures [35, 36, 37, 38, 39, 40]. Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) commonly used objective quality measures but they are widely criticized as well; not correlating well with perceived quality measurement. Universal quality index is one of the new approaches for measuring image quality distortion matrices, which is based on structural distortion measurement instead of error measurement. Universal means the quality measurement approach does not depend on the images being tested, and it is applicable in various image-processing applications and provides a meaningful comparison across the different types of image distortion; the universal quality index Q can be defined as:

$$Q = \frac{4\sigma_{xy}\ \bar{x}\cdot\bar{y}}{(\sigma_x{}^2+\sigma_y{}^2)\,[(\bar{x})^2+(\bar{y})^2]} \quad \ldots (5)$$

Where,

$$\bar{x} = (1/N)\sum_{i=1}^{N} x_i,\ \bar{y} = (1/N)\sum_{i=1}^{N} y_i$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i-\bar{y})^2$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})$$

The dynamic range of Q is lies in between [-1,1]. The best value of 1 is achieved if and only if $y_i=x_i$, for i=1, 2, 3…N. The lowest value of -1 occurs when $y_i = 2\bar{x}-x_i$ for all i=1,2…N. And the values towards 1 give the best results of the resultant image. The quality index is combination of three different factors: loss of correlation, luminance distortion, and contrast distortion. Therefore the Q can be the product of these three components [35].

$$Q = \frac{\sigma_{xy}}{\sigma_x\sigma_y} * \frac{2\overline{xy}}{(\bar{x})^2+(\bar{y})^2} * \frac{2\sigma_x\sigma_y}{\sigma_x{}^2+\sigma_y{}^2} \ldots (6)$$

The first component correlation coefficient, which measures the linear correlation between original and de-noised image, and which is lies in between {-1, 1}. The Second component luminance distortion, which measures the mean luminance between original and de-noised image, and which is lies between {0, 1}. And the third component contrast distortion which measures how similar the contrast in between original and de-noised image, and which lies between {0, 1} [41, 42]

V. Results and Discussion

In this paper we have dealt different orthogonal and bi-orthogonal wavelets through Stationary Wavelet Transform (SWT) on fingerprint images taken from FVC2002 database of size 256x256 to decompose the original image at level 1 to 5. At every level of decomposition we got three detail sub-images (Diagonal, Horizontal and Vertical) and one approximation image is produced. After the decomposition procedure the SURE shrink estimation rigsure, sqtwolog and minimax thresholding methods are applied only on detail sub-images, the noise source of detail images is eliminated at each level. After that, the de-noised detail and approximation image are reconstructed which is free from the noise as shown in figure.
Firstly, we have applied db1 to d10, haar, sym2 to sym8, coif1 to coif5 and bior1.1 to bior5.5 and thresholded them with rigsure with the threshold value 133 from level 1 to 5, at each level the quality and index and computational complexity is predicted. We have achieved the best results for db1 at level- 4, haar at level-4, sym5 at level- 3, coif2 at level-4 and bior1.1 at level-4. Among these wavelets filters db1 at level- 4, haar at level-4 and bior1.1 at level-4 gives the best results. And same experiment is carried out with same images and same wavelet filters by applying the sqtwolog threshold method with a threshold value 4.70964 from level 1 to 5 again at each level the quality index and computational complexity is predicted. We have achieved the best results for db3 at level-5, haar at level-4, sym8 at level-3, coif2 at level 5 and bior1.5 at level-2. Among these sym8 at level-3 gives the best result. And further same experiment is carried out with same images and same wavelet filters by applying the minimax threshold method with a threshold value 3.32 from level 1 to 5 again at each level the quality index and computational complexity is predicted. We have achieved the best results for db2 at level-4, haar at level-2, sym2 at level-4, coif1 at level 3 and bior1.3 at level-4. Among these sym2 at level-3 gives the best result. If we increase the order of filter and the level of decomposition, which are leads to computational complexity and visual quality of the de-noised image. In this work we decomposed the image up to level 5 and the results are shown in Table-1, Table-2 and Table-3 respectively. The level of decomposition increases the quality index of the image will become very poor and image gets blurred. We have got less value of quality index since the image gets distorted; it means that the contrast distortion increases the luminance distortion also gets increased. Through this work we observed that if contrast distortion is poor the negative correlation of the pixel values and quality index of the de-noised image is very low. The observation of the applied wavelet transforms at different decomposition level 1 to 5, the quality index, loss of correlation, luminance distortion and contrast distortion are predicted in Tables and predicted through histogram. It is also observed that there is a variation in quality index for different wavelet types with different order. It is observed that among the three thresholding methods i.e. rigsure with the threshold value 133, sqtwolog threshold method with a threshold value 4.70964 and the minimax threshold method with a threshold value of 3.32. The rigsure with the threshold value 133 for the wavelets db1 at level-4, haar at lvel-4 and bior1.1 at level-4 gives the best results. So, it is very clear that the selection of appropriate wavelet filter and level decomposition plays a crucial role for de-noising the different noises affected on different fingerprint image and it is also observed that no filter performs best for all images.

VI. Conclusion

In this paper we have applied both orthogonal and bi-orthogonal wavelet filters through SWT on fingerprint images at level 1 to 5. After the decomposition procedure the SURE shrink estimation rigsure, sqtwolog and minimax thresholding methods are applied on different fingerprint images with different wavelets. We concluded that the rigsure with the threshold value 133 for the wavelets db1 at level-4, haar at lvel-4 and bior1.1 at level-4 gives the best results.
Finally, we'll note that the quality criterion is very relative depending on the type of images and the scale of the objects in them one may prefer different algorithms. For example, in astronomical images, Medical images, the quality criteria depend on different features, compared to fingerprint images images. De-noising algorithms might be better if they involve not only the noise, but also the image spatial characteristics. And also we conclude that the choice of wavelet filter de-noising of fingerprint images would depends on the type of noise and type of transforms, which are used. The results, which we achieved, are more helpful for Automatic Fingerprint Recognition Systems

(AFRS). Further this work may be extending to detect and de-noise with different type of noises.

Acknowledgement:
This research work is supported by University Grant Commission (UGC), New Delhi, India **(F.No.UGC/MRP(s)/0286/08-09/KAMY022).**
Authors would like thanks to Dr. A. N. Somashekar Principal Grade-II Government College (Autonomous), Mandya –Karanataka-India for providing good infrastructure to carry out this research work.

References

[1] Davide Maltoni, Dario Maio, Anil K. Jain and Salil Prabhakar, "*Handbook of fingerprint recognition*" Springer-Verlag, 2003.
[2] L.C. Jain, U. Halici, I.Hayashi, S.B. Lee, S. Tsutsui, "Intelligent Biometric Techniques in Fingerprint and Face Recognition", by CRC Press LLC, 1999.
[3] RNCOS's Market Research Report "World Biometric Market Outlook (2005-2008)", 22nd March 2006 (IT Market Research)
[4] K. V. Kale, R R Manza, V. T. Humbe and Prapti Deshmukh, "Fingerprint image enhancement using Composite Method", *GSPx-2005 Pervasive Signal Processing Conference,* California USA, 24-27 Oct, 2005.
[5] Ling Hong, Yifei Wan, A.K. Jain, "Fingerprint Image Enhancement: Algorithm and Performance Evaluation", IEEE, Tran. On Pattern Analysis and Machine Intelligence, vol. 20. pp. 777-789, Aug-1998.
[6] Lin Hong, A. K. Jain, Sharth Pankanti, Ruud Bolle, "Fingerprint enhancement", *IEEE in proc. WACA*, PP.202-207, sarasota, FL, 1996.
[7] Louis Coetzee and Elizabeth C. Botha, "Fingerprint Recognition in Low Quality Images", *Pattern Recognition*, vol. 26. No. 10, PP.1441-1460, 1993.
[8] A. K. Hrechak and J. A. McHugh, "Automatic Fingerprint Recognition using Structural Matching", *Pattern Recognition* vol. 23, PP. 893-904, 1990.
[9] Yinpeng Jin, Elsa Angelini and Laine, "*Wavelets in Medical*
    a. *Imaging Processing de-noising, Segmentation and Registration*",
    b. Dept. of Biomedical Engineering, Columbia University New
    c. York, NY, USA.
[10] Mallat S. G., 1989, "*Theory of Multiresoluiton Signal Decomposition: The Wavelet Representation*", IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol.11. No. 7,PP: 674-693.
[11] Buades, A. Coil B Coil, Morel J.M 2005. ," A review of Image De-noising algorithms, with new one", Multiscale model, simulation, Vol.4.No.2,PP:496-530.
[12] Rao M Raghuveer, Bopardikar Ajit S., 2005, "*Wavelet Transform:*
    a. *Introduction to Theory and Applications*", Second Edition, Addison
    b. Wesley publishing Company.
[13] Soman K. P., Ramchandran K.I,2004, "*Insight into WAVELETS from*
    a. *Theory to Practice*", PHI, New Delhi.
[14] Dohono D.L, 1993, "*De-noising by Soft Thresholding*", IEEE Transactions Information Theory, No. 3, PP: 933-936.
[15] Chang S. Grace, Bin Yu and Vattereli M, 2000," *Spatially Adaptive Wavelet thresholding with context modelling for Image de-nosing* ", IEEE Transactions on Image Processing, Vol. 9, PP: 1522-1530.
[16] Gornale S. S, Manza R.R., Humbe Vikas, Kale K.V, 2005, "*Noisy and Noiseless Fingerprint Image Compression using Wavele*t", IT Review Journal of IT and Computer Science, Vol. 01, No. 01, PP 46-50.
[17] Ryeol Kim Il-, 2006, "*Wavelet Domain Partition based Signal Processing with applications to Image De-noising and Compression*", Ph.D. Thesis Delaware University, Springer.
[18] Felix Fernandis,2002, "*Directional, Shift Sensitive Complex Wavelet Transforms with controllable Redundancy*", Ph.D. Thesis, Rice University.
[19] Dilmhani, A.A Madian, N. Maleki , 2002,"*Choice of Wavelet Filter for Medical Image Compression and approximation*", Proceedings of the 2nd Joint EMBS / BMES Conference Houston, TX, USA, 23-26, PP: 1059-1060, ©IEEE
[20] Saha Subhasis and Rao Vermi, 2000, "*Analysis based adaptive wavelet filter selection in lossy image coding Schemes*", ISCAS-2000, IEEE International Symposium on Circuits and systems Genwa, Switzerland, May 28-31.
[21] Wavelet Toolbox guide www.mathsworks.com
[22] Helmi Z. M Shafri and Paul M. Mather, 2005, " *Wavelet Shrinkage in noise Removal of Hyper spectral Remote Sensing Data*", American Journal of Applied Sciences 2(7):1169-1173.
[23] Pesquet J.C., Krim H. and Carfantan H., 1996, "*Time invariant orthonormal Wavelet*

representation", IEEE Transactions on Signal Processing, Vol. 44, PP: 1964-1970.

[24] Warin Chumsamrong and et. al., 1998, "*Using Stationary Wavelet*

[25] *Transform in the classification of SAR images*", 19th Asian Conf.on Remote Sensing, 16-20.

[26] Sukla P. D., 2003, "*Complex Wavelet Transforms and its*

a. *Application*", M.Phil. Thesis, University of Strathclyde, Scotland-

b. UK.

[27] Wang X. H. , Robert S.H. Stephanie, Young Hya, 2003, "*Micro array Image Enhancement by Denoising Using Stationary Wavelet Transform*", IEEE Transactions on Nanobioscience, Vol.2.No4.

[28] Chang S. Grace, Bin Yu and Vattereli M, 2000, " *Adaptive Wavelet thresholding for Image De-noising and Compression*", IEEE Transactions on Image Processing, Vol. 9, PP: 1532-1546.

[29] Panda G., Meher S.K.& Ajhi B.M, 2000, "*Denoising of Corrupted data using Discrete Wavelet Transform*", Journal of the CSI Vol. 30. No.3.

[30] Raghuraman Rangarajan, Ranj Venkataraman, Saha Siddahart, 2002 "*Image de-noising using wavelet*.

[31] Vlodimar P. Melnik, Iiya Shmulevich, Kareen Egiazaranon & Kakko Astola, 2001, "*Block –median Pyramidal transform analysis and de-noising Applications*", IEEE Transactions on Signal Processing, Vol. 49. No.2.

[32] Alle Meije Wink and Jos B.T.M Roeardink,,2004. "*De-noising Functional MR images: A comparison of wavelet De-noising and Gaussian Smoothing*", IEEE Transactions on Medical imaging Vol.23.No.3.

[33] Gonzalez R. C., Woods. R. E. 2004, "*Digital Image Processing*", Second Edition, Pearson Education, New Delhi .

[34] Khalid Sayood,2002, "*Introduction to Data Compression*", Second Edition, Morgan Kaufman publisher .

[35] Salomon David , 2002, "*Data Compression the Complete Reference*", 2nd Edition.

[36] Wang Zhou , Bovik Alan C , 2002, "*A Universal Image Quality Index*", IEEE Signal Processing Letters Vol. 20, No. 7, March .

[37] Gornale S. S, Manza R.R., Humbe Vikas, Kale K.V. 2006, "*Quality Measures of Image Data Compression in Frequency Domain*", Proceedings of International Conference on Sysmetics, Cybernetics, Informatics ICSCI-2006-Hyderabad-India

[38] Klima Milos Jiri Pazderak et.al. 2001, "*Objective and Subjective Image Quality Evaluation for Security Technology*",© IEEE

[39] Martin Bernas, 2002,"*Image Quality Evaluation,* "EURASIP IEEE 8th International Symposium on Video/Image Processing A Multimedia.

[40] Cadik Martin, Slavik Pavel,2004. "*Evaluation of Two Principal approaches to Objective Image Quality Assessment*", Proceedings of 8th International Conference on Information Visualization (IV04) © IEEE

[41] Eskicioglu A. M. and Fisher P.S. 1995, "*Image Quality Measures and Their Performance*", IEEE Transactions on Communications vol. 43,PP: 2959-2965.

[42] Eskicioglu Aglika et.al., 2002, " *Un-decimated Wavelet Transform for image de-noising*" , Dept. of Computer Science, University of Nevada, Reno.

[43] *S.SGornale,VikasHumbe, et. al " Fingerprint Image De-noising through Decimated and Un-decimated Wavelet Transforms(WT) – IEEE Sponsored International Conference Future Computer and Communication (ICFCC 2009) Kualal Lumpur, Malaysia 3-5th April-2009 ISBN: 978-1-4244-3754-2*

Table 1: Shows Quality Index, Loss of Correlation, Luminance and Contrast Distortion with Different
Stationary Wavelet Transform (SWT)
Threshold name: rigsure, Threshold value: 133

Wavelet type	DL*	Quality Index (Q)	Loss of Correlation	Luminance Distortion	Contrast Distortion	Processing Time in seconds
Db1	4	0.997795	1	0.999137	0.998658	0.715
Haar	4	0.997795	1	0.999137	0.998658	0.728
Sym5	3	0.990849	1	0.996955	0.993876	0.807
Coif2	4	0.996509	1	0.99716	0.999347	1.701
Bior1.1	4	0.997795	1	0.999137	0.998658	0.724

* Decomposition Level

Figure-1, Haar at leve-5

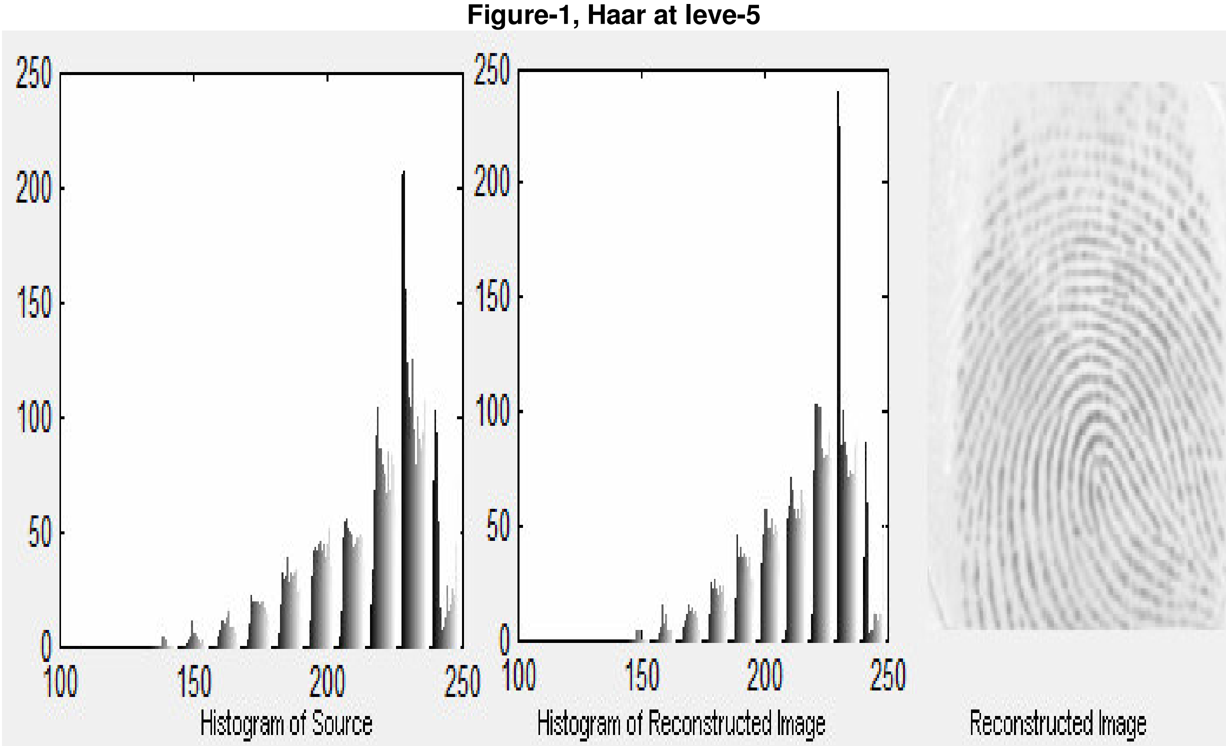

Table 2: Shows Quality Index, Loss of Correlation, Luminance and Contrast Distortion with Different
Stationary Wavelet Transform (SWT)
Threshold name: sqtwolog Threshold value: 4.70964

Wavelet type	DL*	Quality Index (Q)	Loss of Correlation	Luminance Distortion	Contrast Distortion	Processing Time in seconds
Db3	5	0.994252	1	0.995765	0.99848	1.874
Haar	4	0.989636	1	0.990936	0.998687	0.421
Sym8	3	0.995643	1	0.995724	0.999918	1.143
Coif2	5	0.995642	1	0.996407	0.999231	4.288
Bior1.5	2	0.995161	1	0.995977	0.99918	0.517

* Decomposition Level

Figure-2, Db3 at level 5

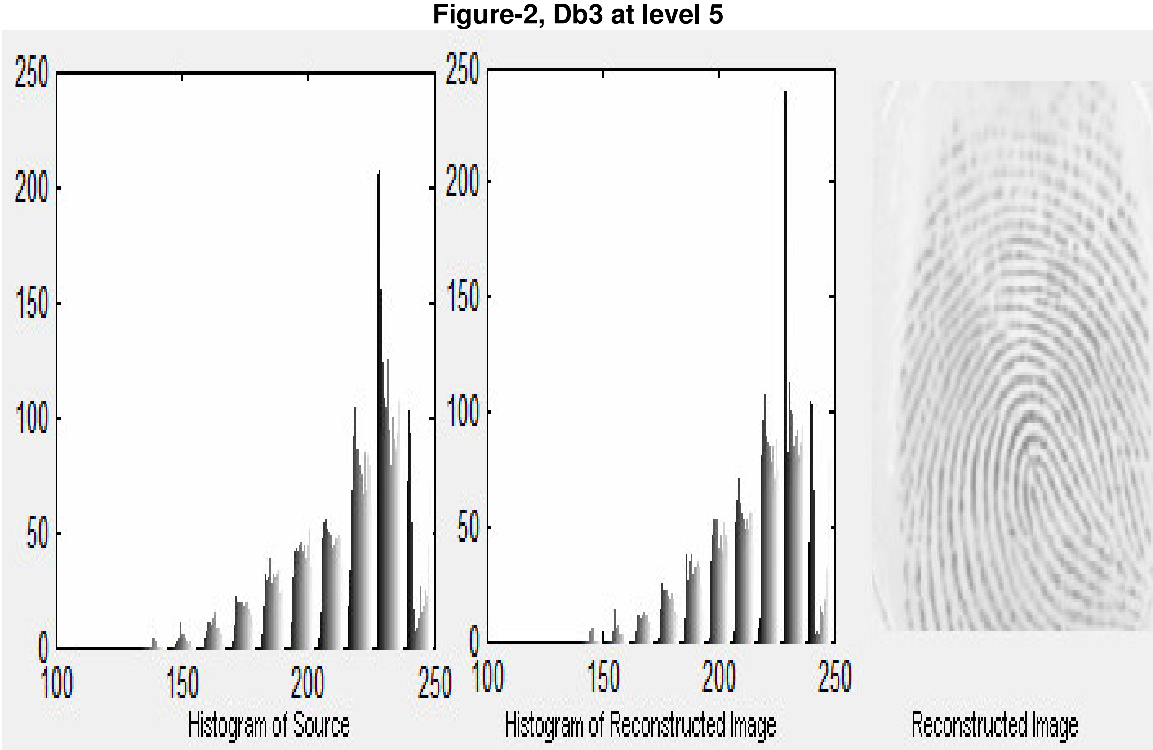

**Table 3: Shows Quality Index, Loss of Correlation, Luminance and Contrast Distortion with Different
Stationary Wavelet Transform (SWT)
Threshold name: minimax Threshold value: 3.32**

Wavelet type	DL*	Quality Index (Q)	Loss of Correlation	Luminance Distortion	Contrast Distortion	Processing Time in seconds
Db2	4	0.994792	1	0.996081	0.998707	0.875
Haar	2	0.757434	1	0.995851	0.76059	0.408
Sym2	4	0.994792	1	0.996081	0.998707	0.877
Coif1	3	0.99362	1	0.996069	0.997542	0.675
Bior1.3	4	0.993741	1	0.995932	0.997799	1.034

* Decomposition Level

Figure-3, Db2 at level-4