International Journal of Engineering Works
Kambohwell Publisher Enterprises
ISSN: 2409-2770 Vol. 4, Issue 12, PP. 104-108, December 2017
www.kwpublisher.com

Reduction of Noise from Fingerprint Images using Stationary Wavelet Trasnform

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***Abstract*—**In Automatic Fingerprint Identification Systems (AFIS) the quality of image is a very important factor as the minutiae extraction from fingerprint image heavily depends on image quality. To enhance the quality of fingerprint images a large number of denoising methods has been used. In this paper fingerprint image enhancement using stationary wavelet transform has been analyzed using different wavelets with different thresholds. Four different wavelets namely Haar DB4 (Daubechies), Coif2 (Coilflets) and Bior1.3 (Biorthogonal) were slected with four thresholds namely VisuShrink, NormalShrink, NeighShrink and BaysShrink. The methods were applied on three types of noises which were Speckle noise, Gaussian noise and Salt and Pepper noise. The effect of changing decomposition level on noise removal efficiency based on PSNR (Peak Signal to Noise Ratio).

***Keywords*—** AFIS, Fingerprints, De-noising, Wavelets, Noise

I. INTRODUCTION

Mostly noise occur in images consists of high frequency components. Low frequencies generally smoothens the image. When spatial and frequency domain filters are applied to these noisy images to remove noise they cut off high frequencies. Sometime the images may com contain high frequency details so removing noise with spatial filtering will also remove these high frequency details. Wavelets transform not only remove noise but also will preserve high frequency details. The image is decomposing into multi resolution representation using SWT as this decomposition not only give the detail about frequency but also gives spatial details. Image is divided into four subbands that are low frequency approximation, high frequency Horizontal vertical and diagonal detail. The details are denoised using soft or hard threshold.

L.Hong et al [1] introduced fingerprint image enhancement technique where frequency and orientation was locally estimated for each pixel. Then on every pixalgabor filter was applied this technique gave satisfactory results. In this method the image is first normalized so it has known mean and variance. So if the fingerprint image contains any distorted gray-level value they are normalized. The gradients in x and y direction was find out by sobel operator which are used to find the orientation fields. These orientation fields are then smoothed if they contain any noise. Finally, orientation frequency is calculated. Gabor filter is tuned to orientation field and orientation frequency. Two methods were introduced by S.Greenberg [2] for fingerprint image enhancement. The first one used histogram equalization locally, which was followed by wiener filter. The image was finally binarized. This method showed improvement in detection of minutia in terms of efficiency. Kale et al [3] proposed de-noising of fingerprint images using composition of stationary wavelet transform and mathematical morphology. These morphological techniques consist of dilation, erosion, opening, and closing. After morphological operation images were further filtered with SWT to enhance the quality. Sherlock [4] introduced directional Fourier filtering. Which reduced complexity compared with Hong method. An improved technique for fingerprint image quality enhancement was proposed by Kim et al [5] which was based on normalization and applying Gabor filter An image is divided into block and region of interest (ROI) of the the image of fingerprint was obtained. Babatunde et al. [6] improved some of the existing algorithm for fingerprint image enhancement.

The new schemes were based on normalizing image, segmentation, estimation of ridge and frequency estimation, Gabor filtering, binarization and finally thinning. Bentley et al [7] described the efficiency of wavelet transform over short term Fourier transforms. As STFT has the deficiency of time frequency resolution which states that time and frequency cannot be utilized simultaneously. I.G. SachinRuiker [8] explained different threshold techniques namely Universal, Visu, Sure, Bayes shrink and normal shrink for de-noising images. Bayes shrink method gave best results. Ma Yinping[9]introduced adoptive thresholding for wavelet decomposition. Different images were de-noised by Baysen shrink technique with soft and hard threshold.

II. TYPES OF THERSHOLDS

Noise contaminates the quality of image either as multiplicative noise or as additive noise. Additive noise as defined as $y(i,j)=s(i,j)+n(i,j)$ while multiplicative noise is defined as $y(i,j)=s(i,j)*n(i,j)$. $S(i,j)$ is the original signal while $y(i,j)$ and $n(i,j)$ are output noisy and noise signal respectively. (i,j) represents the location of the pixel. Gaussian (additive) is equally distributed in every pixel of image. Thus every pixal inthe image is the sum of original value pixel and some Gaussiannoise. In digital images the main cause of Gaussian noise is the acquisition e-g poor illumination causes sensor noise. Salt and pepper noise which is impulsive noise occurs as intensity spikes. As the name suggest it changes the effected pixels into completely dark or bright pixels thus giving the image as salt and pepper like appearance, The unaffected pixels are left unchanged. The cause of salt and pepper noise is analog-to digital conversion error, bit errors in transmission etc. Specklenoise (Multiplicative) degrade every coherent imaging system.Interference between returned waves causes speckle noise inimages.Low frequency contents in image contains slow transitionwhile high frequency contents in image consists of details andedges information. The noise which corrupts the quality ofimage mainly consists of high frequency. So to attenuate highfrequency noise while keep details, some threshold is neededwhich will only suppress noise. Wavelet transform providessuch solution. In wavelet transform an image is separated intofour sub-bands namely HH, HL, LH, LL. lower frequencyapproximation sub-band is represented by LL. While LH, HH,HL shows vertical, diagonal and vertical details respectively.

Soft and hard threshold two widely used thresholds. Discrete wavelet transform has the inefficiency of not being translation invariant. Stationary wavelet transform (SWT) overcome theinefficiency therefore in this paper we have utilized stationarywavelet transform for de-noising. Fig (1) shows denoisingmethod using stationary wavelet trasnform. This is a 2 leveldecomposition in which noisy image is first decomposed intoapproximation LL1 and details LH1, HL1 and HH1. Thresholdis applied on high frequency sub-bands

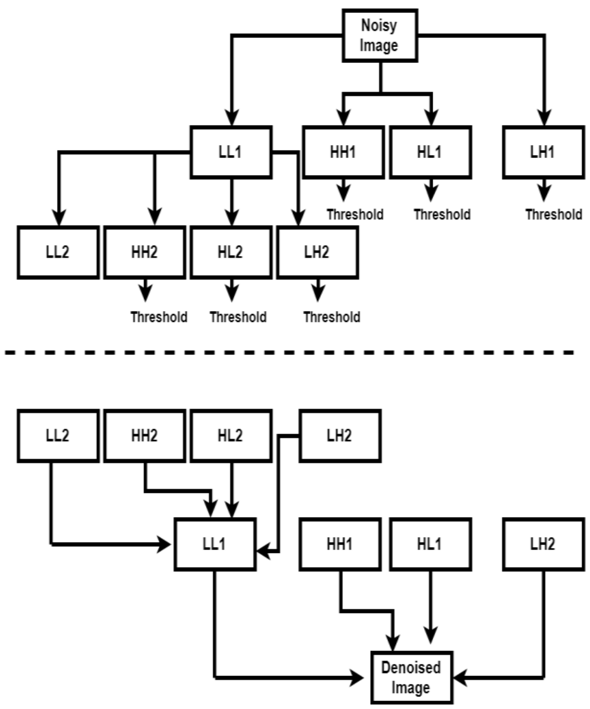

Figure 1. SWT and ISWT at level 2

while Low frequencysub-band is further decomposed into LL2, HH2, HL2 andLH2. Inverse wavelet trasnform is then applied on thresholdedimage to get denoised image.

Soft and hard threshold which are mostly used thresholdsare shown in Figure 2. Soft threshold kill orshrink the noisy pixels while Hard threshold keeps or kill the noisy pixels.

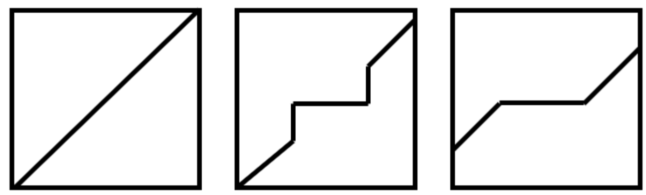

Figure 2. (a) Original signal (b) Hard threshold (c) Soft threshold

A. VisuShrink

Donoho and I. M. Johnstone[10] introduced VisuShrink which is calculated from diagonal sub-band HH1 as:

$$\sigma=\frac{median\ |HH1|}{0.6745} \quad (1)$$

VisuShrink is viewed as general purpose threshold whichdoes not minimize the mean square error but selects nearoptimal threshold. However VisuShrink has a problem of over smoothnessas it kills a large number of high frequency coefficientswhich results in the loss of details and edgeinformation. The other disadvantage is that it is unable toemove speckle noise which is multiplicative noise. It onlyworks fine to deal with additive Gaussian noise.

B. BaysShrink

The Bays[11] shrink which reduces Bayesian risk uses soft threshold and is a sub-band dependent threshold which means that at each sub-band and decomposition level threshold is done. The Bayes threshold Tb is defined as:

$$T_B=\frac{\sigma^2}{\sigma s} \quad (2)$$

Where $\sigma^2$is variance of noise which is calculated from equation (1) σsis the variance of signal. As the noise and the signal are independent of each other which is given by:

$$\sigma n^2=\sigma s^2+\sigma^2 \quad (3)$$

whereσ$n^2$is defined as:

$$\sigma n^2=\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N} I(i,j)^2 \quad (4)$$

where M*N shows the number of pixels in image I Finally, the signal variance σs^2 is calculated as:

$$\sigma s^2=\sqrt{\max(\sigma n^2-\sigma^2),0} \quad (5)$$

For one decomposition level there are three different thresholdscalculated for diagonal, vertical and horizontal sub-band. Similarlyfor further decomposition level threshold is calculatedfor each sub-band at every level.

C. NormalShrink

Normal Shrink TN is defined as:

$$T_N = \lambda \frac{\sigma}{\sigma std} \tag{6}$$

Where λ is defined as:

$$\lambda = \sqrt{\log(Lk/L)} \tag{7}$$

In above equation LK shows the length of kth scale sub-band while L shows total number of decomposition levels. σis the variance of noise which is already defined in equation (3). similarly the standard deviation σstdof sub-band of noisysignal can be found using equation (4). Soft threshold isperformed with NormalShrink.

D. NeighShrink

NeighShrink uses sliding window operation to shrink thenoisy values. A window of LxL size is created and thencentral pixel in the window is replaced by new value. Window is then moved one pixel forward and same operation is applied on all pixels. It is also band dependent shrinkage rule and shrinkage is applied at every sub-band of decomposition level. If B(i,j) is the window and w(i,j) is the central pixel thenthe pixel w(i,j) is replaced by W(i,j) as:

$$W(i,j) = w(i,j)*B(i,j) \tag{8}$$

whereB(i,j)is known as shrinkage factor and is defined as:

$$B(i,j) = 1 - \frac{TU^2}{s(i,j)^2} \tag{9}$$

For a window size of 3x3 s(i,j)is defined as:

$$s(i,j) = \sum_{i=1}^{M} \sum_{j=1}^{N} w(i,j)^2 \tag{10}$$

TU is also known as Universel [12] threshold and is calculated as :

$$TU = \sqrt{2\sigma \log(n)} \tag{11}$$

where n shows the size of signal.

Image is divided into high and low frequency band and above operation window operation is applied on all high frequency bands. Thus replacing each pixel value in HH, HL and LL. Finally inverse stationary wavelet transform is applied on LL, HH, HL, LH to get demised image.

III. RESULTS

The method used in this paper to denoise noisy fingerprintimages has been implemented in MATLAB. While theimages of fingerprints are acquired from Nist database. Thethreshold selected are VisuShrink, BaysShrink, NormalShrinkand NeighShrink.While selected wavelets are Haar, DB4(Daubecheis), Coif2 (Coiflets) and Bior1.3 (Biorthogonal).These methods are tested on fingerprints images which containedGaussian noise, speckle noise and salt pepper noise.To evaluate the performance of the proposed technique performanceevaluation metrics like PSNR(Peak Signal to Noise Ratio). MSE measures the difference between input reference and output processed images.It is given by following equation:

$$MSE = \frac{1}{M*N} \sum_{i=1}^{M} \sum_{j=1}^{N} (s(i,j) - x(i,j))^2 \tag{12}$$

Where s(i,j) is the output de-noised image while x(i,j) is the input reference image

A. PEAK SIGNAL TO NOSIE RATIO

It measures the reconstruction quality and is given by:

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{13}$$

VisuShrink, NormalShrink and BaysShrink performed wellat decomposition level of 2. While NeighShrink performancewas degraded at higher level. Therefore, in below figures exceptNeighShrink whose values are noted at level 1, all othervalueslisted are at decomposition level at 2.To remove Gaussian and speckle noise the best result wasprovided by BaysShrink at level 2 when combined with Haarwavelet.Similarly Salt pepper noise was effectively reducedby NeighShrink at level 1 when combines with Haar wavelet.Following figures shows the result.

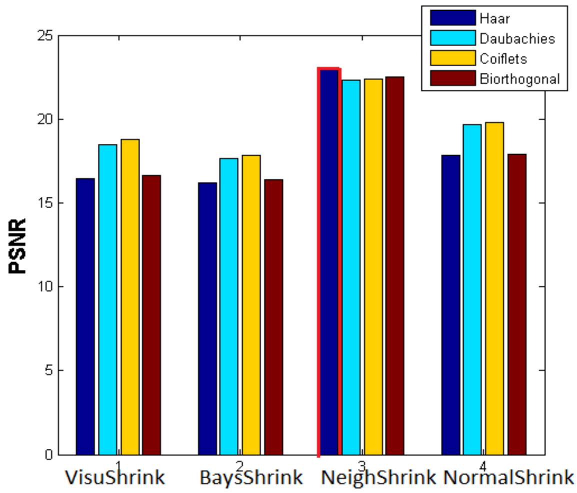

Figure 3. Gaussian noise reduction using different thresholds

Figure 3 Shows the reduction of Gaussian noise using different thresholds. Every threshold was implemented with different wavelet families such as Haar, Daubechies, Coiflets, and Biorthogonal

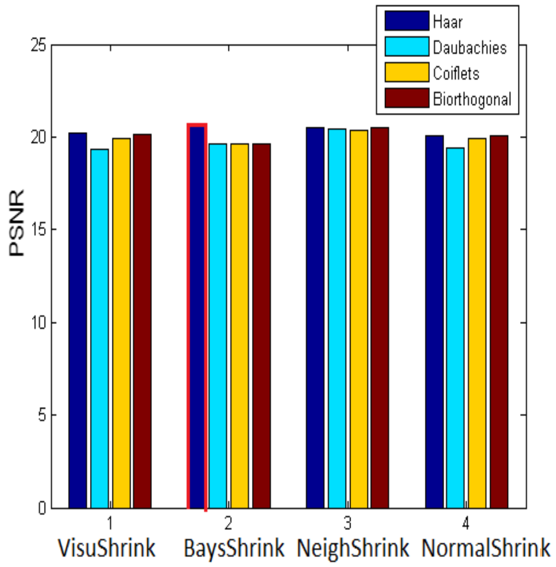

Figure 4. Salt & Pepper noise reduction using different thresholds

Figure. 4 shows the reduction of Salt and pepper noise uing different thresholds. The figure depicts that NeighShrink threshold when combined when Haar wavelet provides best result. On the other hand, VisuShrink did not provided satisfactory result in the reduction of salt and pepper noise from noisy fingerprint image.

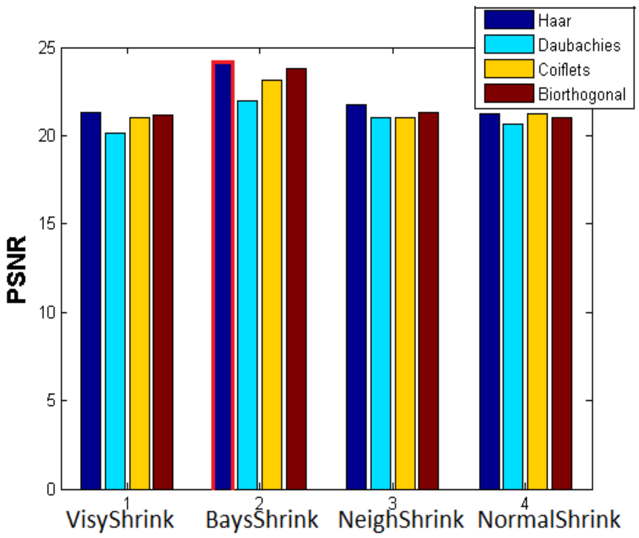

Figure 5. Speckle noise reduction using different thresholds

Figure 6 shows original and noisy images. Fig 6(a) is original image, different noise are added to that image. All images contain zero mean noise with variance of 0.05.

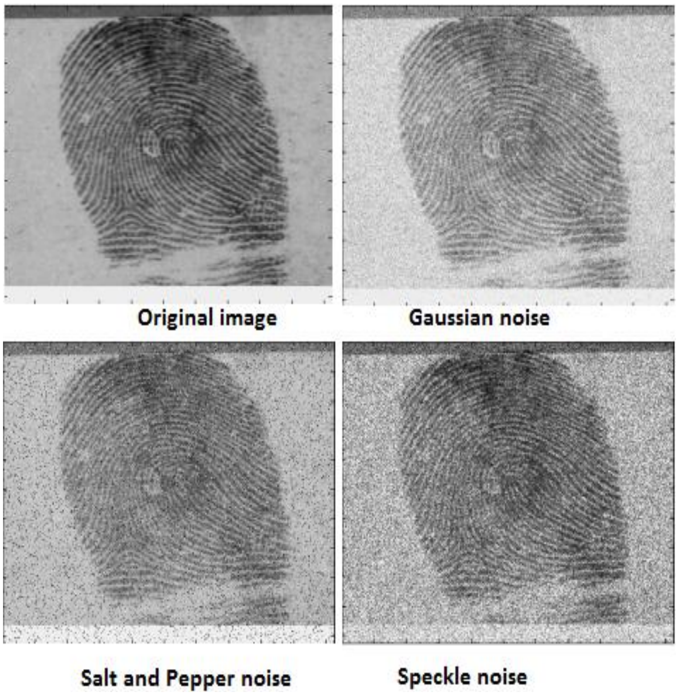

Figure 6. Original image contaminated by different types of noise

Fig 7 shows the reduction of Gaussian noise using different thresholds and different wavelets. Figure 7(a) shows best result for reduction of Gaussian noise. Bays threshold when combined with Haar wavelet has removed Gaussian noise effectively as compared with other techniques.

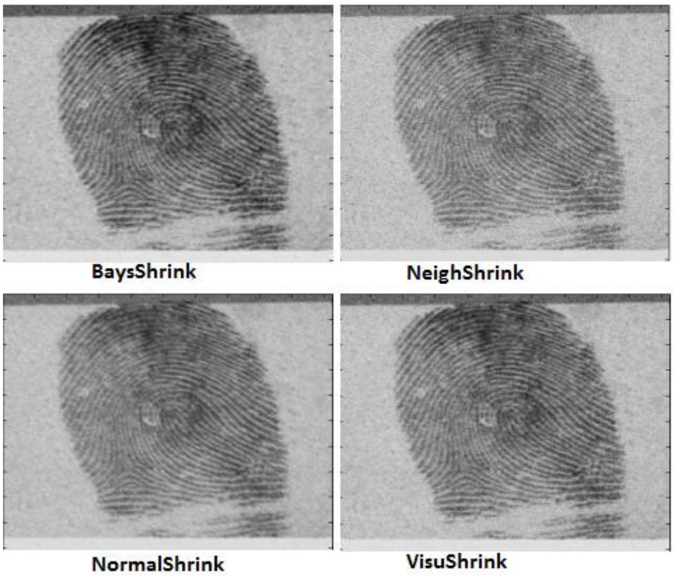

Figure 7. Reduction of Gaussian noise

Figure 8 Shows reduction of Speckle noise using different techniques.

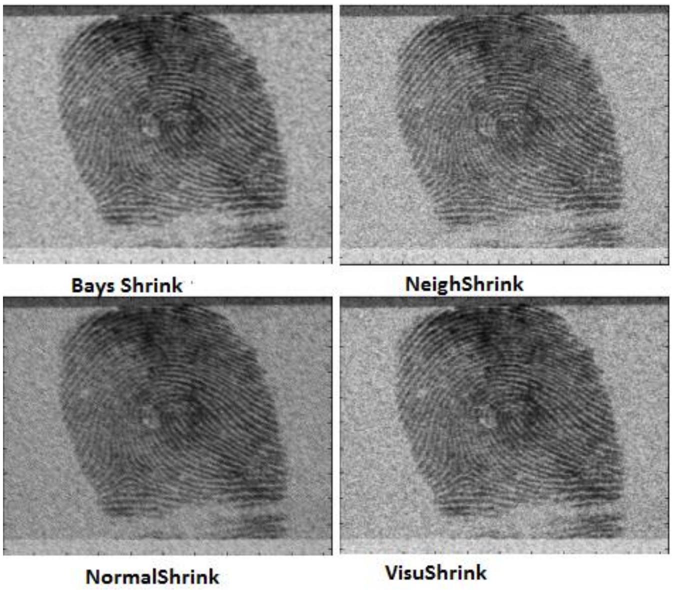

Figure 8. Fig. 8 Reduction of Speckle noise

Finally, Fig. 9 shows the reduction of salt and pepper noise using different thresholds combined with different wavelets. The figures shows that best result was provided by NeighShrink when combined with Haar wavelet. While NormalShrinkdid not provided satisfactory result in the reduction of salt and pepper noise.

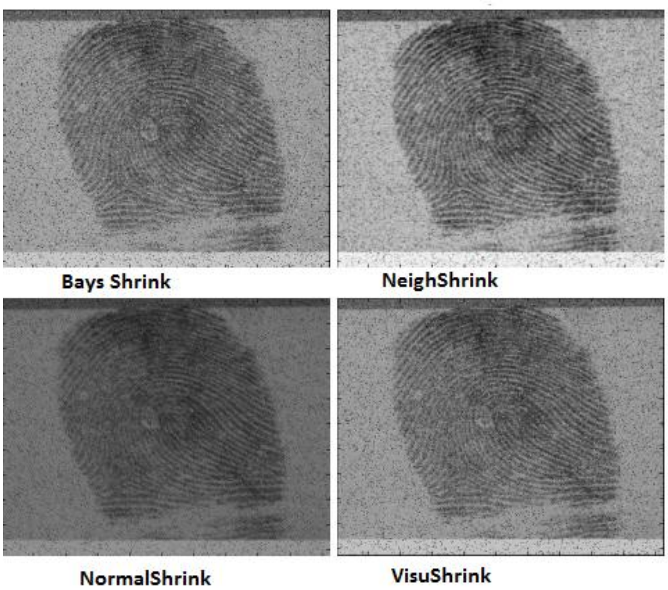

Figure 9. Fig. 9 shows the reduction of salt and pepper noise

CONCLUSION

In this paper, the fingerprint image was restored which contained different types of noise such as multiplicative and additive. Stationary wavelet transform was applied on these images to reduce noise from these images. Different types of thresholds ware applied to remove to remove different types of noise. To reduce Gaussian nioseBaysShrink when combined with Haar wavelet provides best result. Similarly, Speckle noise was also reduced effectively by Haar wavelet and BaysShrink. Salt and Pepper noise was reduced effectively by NeighShrink.

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ISSN: 2409-2770