A Comparative Study of Wavelet Transform based Denoising Techniques for Latent Fingerprints*

Abstract. Latent fingerprints serve as crucial evidence for law enforcement agencies to punish perpetrators. They are found in almost every crime scene. Conventionally, latent fingerprint have been obtained using destructive methods such as chemicals, dyes and tapes to lift the print sample. These conventional methods contaminate the sample and leave no room for further processing, such as touch DNA. In recent years, the forensic community has been moving towards the use of contactless techniques to acquire latent fingerprints. Contactless acquisition surpasses destructive techniques by allowing multiple acquisitions of the sample and secondary pre-processing of the sample. Moreover, there are cases where the conventional methods fail; such as acquiring fingerprints deposited on thin layers of plastic, fingerprints sandwiched between duct tapes. For such reasons, Optical coherence tomography (OCT) is one of the new technologies that are correctly being investigated for latent fingerprint acquisition. The OCT technology, however, does present some technical challenges as a fingerprint sensor. The images that are produced by OCT are often immersed in speckle noise. Seven most recent wavelet-based denoising techniques (VisuShrink, BayesShrink, SureShrink, NormalShrink, Modified VisuShrink, Minimax and Adaptive Threshold method) have been investigated with the aim to find a way to suppress speckle noise on OCT fingerprint images. Experimental results have shown that adaptive thresholding method has superior performance compared to other wavelets techniques in terms of signal to-noise-ratio (SNR).

Keywords: Denoising · Fingerprints · Wavelet Thresholding · Biometrics · Optical Coherence Tomography

1 Introduction

In a crime scene latent fingerprints are finger impressions left unintentional by the contact of a human finger with a surface of an object. These impressions serve as crucial evidence for law enforcement agencies to punish perpetrators. These type of fingerprints are found in almost every crime scene and traditionally collected using destructive methods.

Destructive methods of lifting latent fingerprints include but not limited to chemicals, dyes and adhesive tapes. These conventional destructive methods contaminate the sample and leave no room for further processing, such as touch

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DNA and drugs analysis. In recent years the forensic community has been moving towards the use of contactless techniques to acquire latent fingerprints.

Contactless acquisition methods of acquiring latent fingerprints include but not limited to chromatic white light sensor, alternative light sources, infrared sensors and Optical coherence tomography (OCT) [11, 5, 11, 3, 2]. These contactless acquisition methods pose some advantages over destructive methods; such as allowing multiple acquisitions of the sample and secondary pre-processing of the sample. Additionally, there are cases where traditional methods completely fail; such as acquiring fingerprints deposited on thin layers of plastic, fingerprints sandwiched between duct tapes. For such reasons, OCT is one of the new technologies that are currently being investigated for latent fingerprint acquisition. The OCT technology, however, does present some technical challenges as a fingerprint sensor. The images that are produced by OCT are often immersed in speckle noise.

An image may be corrupt by noise during acquisition and transmission. Noise degrades the quality of the image by interfering with the original image signal, which results in the variation of pixels. The noise signal may appear as additive or multiplicative on an image [12, 11]. Additive noise signal includes impulse noise, Salt & Pepper noise and Gaussian white noise, while the multiplicative noise signal includes speckle noise. Any unwanted modifications of a signal or image are called noise. Noise may be suppressed by the process called denoising.

Denoising is the process of reducing noise from the signal. A signal can be any gesture, action or sound that is used to convey information. In image processing, a signal is an image. Image denoising is essential for better performance of any authentication system. Noise removal on fingerprint images unmask important details such as ridges endings and valleys and minimize the processing time for subsequent operations. Various techniques for fingerprint image denoising have been developed [9, 16, 4, 13].

In this paper, wavelet transform based techniques are implemented in an effort to remove speckle noise from the latent fingerprint images acquired using OCT system. These techniques combined with different wavelet filters are compared in terms of speckle noise removal and signal-to-noise ratio (SNR) is used as the quantitative measure of that. The compared techniques are VisuShrink, BayesShrink, SureShrink, NormalShrink, Modified VisuShrink, Minimax and Adaptive Threshold method. The wavelets filters used are haar, db2, db4 and sym4. These techniques and wavelets filters were carefully selected from the literature [9, 16, 4, 13] as they give positive results in terms of speckle noise removal.

2 Data Acquisition

2.1 Optical Coherence Tomography

In this work, latent fingerprints were acquired from, brass (door handle), stainless still (knife) and glass. A custum made spectral domain OCT system with the specifications on table 1 was used.

Table 1: Shows the specifications of the customized latent fingerprint OCT acquisition device.

Base Unite	**GAN610**
Central Wavelength	930 nm
Average Power	10 mW
Axil Scan rate	50, 100, 200 and 248 kHz
Imaging Depth	2.9 mm
Scanning Lens	**Key Specifications**
Effective Focal Length	110 mm
Maximum Scannable Area	28.9×28.9 mm^2

2.2 Acquisition Process

- A finger was placed on each substrate to leave a fingerprint impression. The OCT system would start acquiring a print impression left on the substrates.
- The OCT machine produces a 3D volume data per fingerprint. The 3D data must then be project into a 2D fingerprint image

3 Wavelet Transform

If an image convolves with low pass and high pass filter in the vertical and horizontal direction, four sub-images of the original image are formed [16]. The sub-image encompasses the full image, but at different resolutions and containing different components of the original image. This includes a sub-image of low frequency in both the horizontal and vertical direction (LL), sub-image with low horizontal frequency but high vertical frequency (LH), sub-image with high horizontal frequency but low vertical frequency (HL) and (HH) which has high frequency in both horizontal and vertical directions. Fig. 1 shows the decomposition skeleton of the image up to level 2, where LL is the approximation image, HL, LH and HH represent image details in the horizontal, vertical and diagonal direction respectively, the subscript represents the decomposition level. The discrete wavelet transform (DWT) and stationary wavelet transform (SWT) are well known transforms that are used to transform or to split the image in to four components (LL, HL, LH and HH) [16, 17].

3.1 Soft and Hard Thresholding

Image thresholding is the technique used to partition an image into background and foreground [6]. It is simple and mostly used where ever two regions need to be separated or distinguished. In wavelet transform, thresholding is done on one wavelet coefficient at a time [6]. Each coefficient is compared to the threshold value depending on thresholding rules, which are hard and soft thresholding.

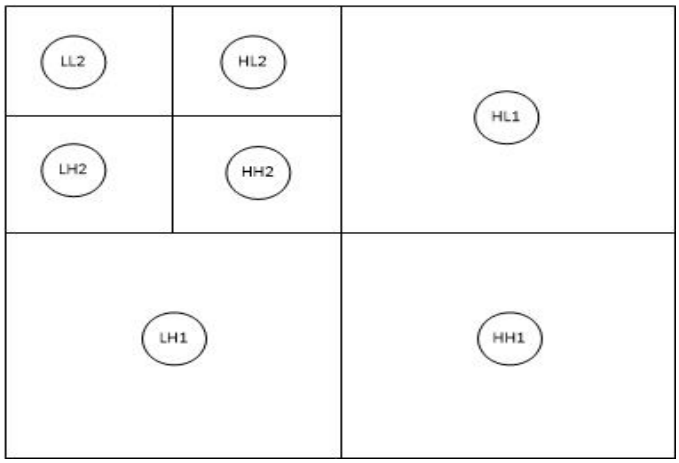

Fig. 1: Image wavelet decomposition.

All coefficients in hard thresholding are either zero or greater or equal to the threshold value, as shown in (1) [1].

$$f(x)_h = \begin{cases} x, & \text{if } |x| \geq T \\ 0, & \text{if } |x| < T \end{cases}, \tag{1}$$

where, T, is the threshold value, for soft thresholding, wavelets coefficients are reduced to a threshold value as shown in equation (2) [1, 14].

$$f(x)_s = \begin{cases} x - T, & \text{if } |x| > T \\ 0, & \text{if } |x| \leq T \\ x + T, & \text{if } |x| > -T \end{cases} \tag{2}$$

4 Wavelets Denoising Techniques

The following wavelets denoising techniques have been implemented on MATLAB for fingerprint images captured using the OCT system. Haar, db2, db4, sym4 wavelet filters have been used for these techniques and the decomposition level 1, 2, 3 and 4 were chosen. Fig. 2 shows the wavelet transform based denoising procedure used in this work. In this work adaptive histogram equalization was used as the pre-processing technique. The SNR is used for quantitative analysis of the techniques (VisuShrink, BayesShrink, SUREShrink, NormalShrink, modified universal threshold and adaptive threshold Shrink) implemented in this work. The SNR is the measure used in science and engineering to compare the level of desired signal to the level of background, it is defined as follows:

$$SNR = \frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} F(x,y)^2}{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[G(x,y)^2 - F(x,y)^2]}, \tag{3}$$

where $F(x,y)$ is the denoised image and $G(x,y)$ is the corrupted image.

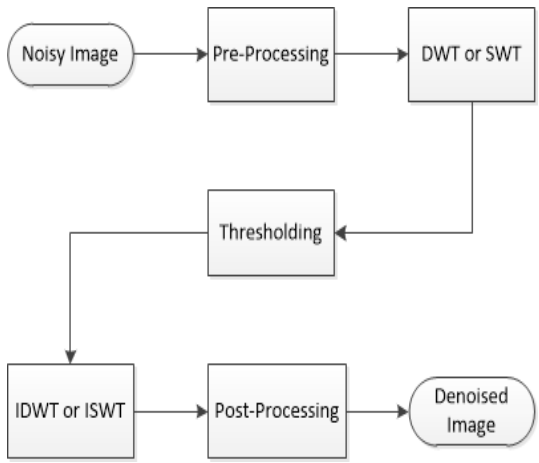

Fig. 2: The basic structure of wavelet transform based image denoising

4.1 VisuShrink

VisuShrink also known as universal threshold is the thresholding technique which does not minimize the mean square error but picks an optimal threshold near by [**?**,**?**]. Universal threshold is computed from diagonal subband HH1 as,

$$\sigma = \frac{median|HH1|}{0.6745}. \tag{4}$$

The actual threshold value is calculated as:

$$T = \sigma\sqrt{2logM}, \tag{5}$$

where M is the number of pixels in an image. However, universal threshold is less effective in removing multiplicative noise such as speckle noise.

4.2 BayesShrink

BayesShrink is a subband dependent threshold. This means that at each subband (*i.e.* HL1, LH1 and HH1) and decomposition level threshold value is computed and thresholding is done [10, 7]. The Bayes threshold is computed using (6):

$$T = \frac{\sigma^2}{\sigma_s}, \tag{6}$$

where σ^2 is noise variance given by (4) and σ_s is the variance of noise free image. Since the noise and the signal are mutually independent, their variance is modelled as:

$$\sigma_y = \sigma_s + \sigma \tag{7}$$

where σ_y is computed as,

$$\sigma_y^2 = \frac{1}{M^2} \sum_{i=1}^{M} \sum_{j=1}^{M} I(i,j)^2, \tag{8}$$

where M is the number of pixels in image I. Then σ_s on (6) is computed as

$$\sigma_s = \sqrt{(max(\sigma_y^2 - \sigma^2), 0)} \tag{9}$$

4.3 SureShrink

SureShrink applies thresholding by applying a subband adaptive threshold. An optimal threshold is computed separately for each detail sub-band based upon Stein's Unbiased Risk Estimator (SURE) [14, 15]. The optimal threshold on level k with soft thresholding is defined as:

$$t_k^s = argmin_t SURE(t; x) \tag{10}$$

where t_k^s is estimated from decomposition coefficients and x is the set of noisy wavelet coefficients in a subband.

4.4 NormalShrink

NormalShrink technique is a wavelet domain denoising method based on the generalized Gaussian distribution(GGD) subband coefficients modelling [10]. The threshold value of NormalShrink is defined as

$$T = \beta \frac{\sigma^2}{\sigma_y}, \tag{11}$$

where σ^2 is noise variance given by (4). The σ_y is the standard deviation of the noisy signal which is computed using (8). The β constant is the scale parameter which is computed as

$$\beta = \sqrt{log\left(\frac{L_k}{J}\right)}, \tag{12}$$

where L_k is the length of the sub-band and J is the total number of decomposition levels. The normalShrink technique outperforms both Bayes and visuShrink noise removal methods, it preserves edges efficiently [8].

4.5 Modified Universal Threshold

The difference between Modified universal threshold and universal threshold is that instead of 2 a Golden ratio value (1.618) is used, then the threshold is computed as:

$$T = \sigma\sqrt{(1.618)logM} \tag{13}$$

4.6 Adaptive Threshold

The adaptive threshold proposed in [16] is similar to BayesShrink by setting different threshold for every subband. The difference is the threshold computation, BayesShrink is shown in subsection B, while the adaptive threshold is given as,

$$T = \begin{cases} \frac{\sigma^2_{W_\Phi}(i)}{\sigma_{W_F}(D,i)} & \text{if } \sigma_{W_F}(D,i) \neq 0 \\ max(W_{x,y}(D,i)) & \text{if } \sigma_{W_F}(D,i) = 0 \end{cases}, \tag{14}$$

where $i = 1, 2, ..., k$ represents wavelet decomposition layers. $D = 1, 2, 3$ and it represents horizontal, vertical and diagonal details respectively. The standard deviation of the noisy image is defined as:

$$\sigma_{W_F}(D,i) = \sqrt{max(\sigma^2_{W_G}(D,i) - \sigma^2_{W_\Phi}(i), 0)} \tag{15}$$

The standard deviation , σ_{W_Φ}, of noise signal is estimated using the median estimator is computed as:

$$\sigma_{W_\Phi} = \frac{median(|HH_i|)}{0.6745}, \tag{16}$$

and the image signal noise variance is given by:

$$\sigma^2_{W_G}(D,i) = \frac{1}{N(i)^2}\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} W_G(D,i), \tag{17}$$

where $N(i)$ is the number of pixels at different sub-images and $W_G(D,i)$ represent wavelet coefficients at different details and decomposition levels.

5 Experimental Results

The techniques discussed on section 4 were implement on MATLAB and the images in Fig. 3, shows the experimental results of this techniques. Table 2 to 5 shows the quantitative performance of these denoising techniques as SNR.

Table 2: Shows the SNR value for each technique with a certain wavelet filter at decomposition level 1.

	haar	db2	db4	sym4
VisuShrink	45.3085	46.1545	48.4594	47.8388
BayesShrink	46.1707	46.1549	46.1566	46.1979
Minimax	46.1908	46.1458	45.6900	47.4162
SureShrink	46.1952	46.1260	45.8923	46.1428
NormalShrink	38.2592	44.7893	48.7715	47.6175
Modified VisuShrink	41.0928	47.3135	36.7069	42.5330
Adaptive Threshold	40.9145	**48.6533**	42.8866	41.4479

Table 3: Shows the SNR value for each technique with a certain wavelet filter at decomposition level 2.

	haar	db2	db4	sym4
VisuShrink	46.1795	46.1418	38.8561	47.6953
BayesShrink	46.1599	46.1554	42.3661	44.9396
Minimax	**50.5541**	46.1557	44.6618	47.1494
SureShrink	46.0642	46.1556	45.8930	46.2126
NormalShrink	36.8723	39.2311	48.3460	47.0376
Modified VisuShrink	41.0933	46.6277	42.6166	42.4867
Adaptive Threshold	40.9145	48.6533	42.8866	41.4479

6 Discussion

The OCT system has successfully acquired latent fingerprints from glass, stainless steel and brass (door knob). Fig. 3a shows the latent fingerprint image acquired from the stainless steel and Fig. 3b to Fig. 3h shows the images of the denoised version of original image using different denoising discussed in previous sections. Table 2, 3, 4 and 5 shows SNR results at different levels with different wavelet filters of the implemented techniques.

On Table 2 where the decomposition level equals to one, the adaptive threshold method combined with db2 wavelet filter outperform other denoising techniques with the value of SNR = 48.6533. The minimax denoising technique at decomposition level 2 combined with haar surpass the other denoising techniques (on Table 3)) with a value of SNR = 50.5541, however, minimax technique does not give good image according to the human visualization system. The normalShrink on Table 4 combined with sym4 at level 3 outperforms the other denoising techniques, the issue with normalShrink is that speckle noise is not removed effective. On Table 5 the adaptive threshold combined with db2 is optimal with an SNR = 48.6533.

It is observed that from Table 2 to 5 the SNR value for the adaptive threshold is constant. The constant SNR value is due to the how noise is estimated on an image. The median estimator which is used to estimate noise becomes very small in high levels, this suggests that the technique is effective at lower levels and that

Table 4: Shows the SNR value for each technique with a certain wavelet filter at decomposition level 3.

	haar	db2	db4	sym4
VisuShrink	46.1294	46.1580	45.3769	46.7925
BayesShrink	46.1967	46.1965	46.0154	45.9201
Minimax	46.1785	46.1999	45.7994	45.9943
SureShrink	46.1787	46.1529	45.8760	46.2129
NormalShrink	47.7042	36.5891	**48.6539**	41.2657
Modified VisuShrink	41.2158	46.6278	42.8355	42.4868
Adaptive Threshold	41.0589	48.6533	42.8866	41.4479

Table 5: Shows the SNR value for each technique with a certain wavelet filter at decomposition level 4.

	haar	db2	db4	sym4
VisuShrink	46.1233	46.1585	44.9114	45.7159
BayesShrink	46.1766	46.2223	45.8630	46.1578
Minimax	45.8998	46.1983	45.2014	46.0012
SureShrink	45.9786	46.1559	46.1547	46.0824
NormalShrink	36.0265	34.9886	38.1440	39.6825
Modified VisuShrink	41.2164	46.6277	42.6894	42.1665
Adaptive Threshold	41.0557	**48.6533**	42.8866	41.4479

is the goal of many wavelet denoising techniques since high are computational expensive and distort images most of the time.

The adaptive threshold method combined with db2 method may be further enhanced to yield much better results. Adaptive threshold is derived from VisuShrink and BayesShrink, therefore modifield universal threshold can be combined with adaptive threshold since modified universal threshold is derived from Visushrink. This combination may give better results of the modified universal threshold according to the results on Table 2 to 5.

7 Conclusion and Future Work

The combination of adaptive threshold and db2 filter at level 2 or 4 decomposition remove speckle noise on OCT latent fingerprint images better then the other denoising techniques in this work. In future the adaptive threshold method will be modified to yield much better results.

References

1. Al Jumah, A.: Denoising of an image using discrete stationary wavelet transform and various thresholding techniques. Journal of Signal and Information Processing **4**(01), 33 (2013)

2. Crane, N.J., Bartick, E.G., Perlman, R.S., Huffman, S.: Infrared spectroscopic imaging for noninvasive detection of latent fingerprints. Journal of forensic sciences **52**(1), 48–53 (2007)
3. Dakshinamurthy S, P.K.A.: Study on efficiency of alternate light source for detection of latent fingerprints (2018)
4. Darlow, L.N., Akhoury, S.S., Connan, J.: A review of state-of-the-art speckle reduction techniques for optical coherence tomography fingertip scans. In: Seventh International Conference on Machine Vision (ICMV 2014). vol. 9445, p. 944523. International Society for Optics and Photonics (2015)
5. Dubey, S.K., Mehta, D.S., Anand, A., Shakher, C.: Simultaneous topography and tomography of latent fingerprints using full-field swept-source optical coherence tomography. Journal of Optics A: Pure and Applied Optics **10**(1), 015307 (2008)
6. Hedaoo, P., Godbole, S.S.: Wavelet thresholding approach for image denoising. International Journal of Network Security & Its Applications (IJNSA) **3**(4), 16–21 (2011)
7. Iqbal, N.: Reduction of Noise from Fingerprint Images using Stationary Wavelet Trasnform. International Journal of Engineering Works (ISSN: 2409-277) **4**(12), 104–108 (Dec 2017). https://doi.org/10.5281/zenodo.1133286
8. Kaur, L., Gupta, S., Chauhan, R.: Image denoising using wavelet thresholding. In: ICVGIP. vol. 2, pp. 16–18 (2002)
9. Kaur, S.: Noise types and various removal techniques. International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE) **4**(2), 226–230 (2015)
10. Leavline, E.J., Sutha, S., Singh, D.A.A.G.: Wavelet domain shrinkage methods for noise removal in images: A compendium. International Journal of Computer Applications **33**(10), 28–32 (2011)
11. Leich, M., Kiltz, S., Dittmann, J., Vielhauer, C.: Non-destructive forensic latent fingerprint acquisition with chromatic white light sensors. In: Media Watermarking, Security, and Forensics III. vol. 7880, p. 78800S. International Society for Optics and Photonics (2011)
12. Maity, A., Pattanaik, A., Sagnika, S., Pani, S.: A comparative study on approaches to speckle noise reduction in images. In: Computational Intelligence and Networks (CINE), 2015 International Conference on. pp. 148–155. IEEE (2015)
13. Makinana, S., Khanyile, P.N., Khutlang, R.: Latent fingerprint wavelet transform image enhancement technique for optical coherence tomography. In: 2016 Third International Conference on Artificial Intelligence and Pattern Recognition (AIPR). pp. 1–5 (Sep 2016). https://doi.org/10.1109/ICAIPR.2016.7585203
14. Nasif, H.: Wavelet denoising (04 2016). https://doi.org/10.13140/RG.2.1.1074.9844
15. Xiao, F., Zhang, Y.: A comparative study on thresholding methods in wavelet-based image denoising. Procedia Engineering **15**, 3998–4003 (2011)
16. Yinping, M., Yongxing, H.: Adaptive threshold based on wavelet transform fingerprint image denoising. In: Proceedings of the 2012 International Conference on Computer Science and Electronics Engineering - Volume 03. pp. 494–497. ICCSEE '12, IEEE Computer Society (2012). https://doi.org/10.1109/ICCSEE.2012.139
17. Zaki, F., Wang, Y., Su, H., Yuan, X., Liu, X.: Noise adaptive wavelet thresholding for speckle noise removal in optical coherence tomography. Biomed. Opt. Express **8**(5), 2720–2731 (May 2017). https://doi.org/10.1364/BOE.8.002720

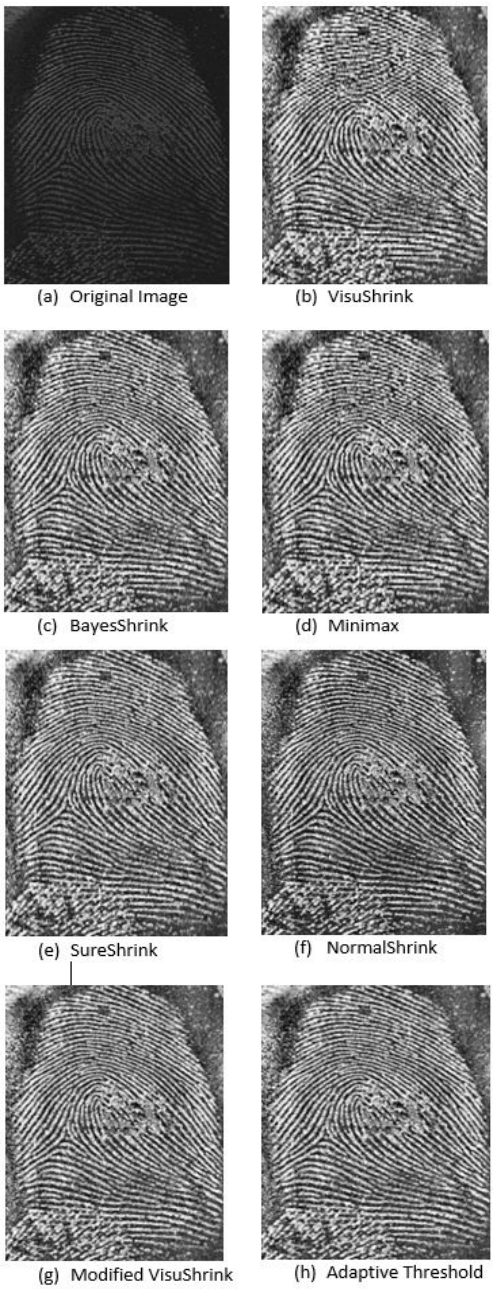

Fig. 3: (a) noisy original fingerprint image, (b) Denoised by Visushrink, (c) Denoised by BayesShrink, (d) Denoised by Minimax, (e) Denoised by SureShrink, (f) NormalShrink, (g) Modified VisuShrink and (h) Denoised by adaptive threshold.