Speckle Noise Removal from Latent Fingerprint Images*

Abstract. Latent fingerprints serve as crucial evidence for law enforcement agencies to punish perpetrators. They are found in almost every crime scene. Conventionally, latent fingerprints have been obtained using chemicals or physical methods, thus destructive techniques. Forensic community is moving towards contactless acquisition methods. The contactless acquisition presents some advantages over destructive methods; such as advantages include multiple acquisitions of the sample and a possibility of further analysis such as touch DNA. Examples of contactless fingerprint acquisition technologies are digital cameras, chromatic white light sensor and optical coherence tomography(OCT). In this work, OCT is used to acquire latent fingerprint images. However, OCT images are often immersed in speckle noise, therefore in this work, a modification of the adaptive threshold method for speckle noise removal on OCT latent fingerprint images is proposed. Experimental results have shown that the proposed modified adaptive thresholding method has superior performance compared to the adaptive threshold techniques in terms of peak signal-to-noise ratio (PSNR) and root mean square error (RMSE).

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

1 Introduction

Latent fingerprints are finger marks left on the surface of an object when a finger comes into contact with that object. This type of prints are found in almost every crime scene, and they serve as an important piece of evidence for law enforcement agencies to sentence culprits. Traditionally, latent fingerprints have been lifted using chemicals or instruments that are destructive. The destructiveness of traditional method presents some serious disadvantages; such as contaminating the sample, which hinders further analysis such as touch DNA and drags analysis; as a result, the legal community is moving towards contactless acquisition methods.

The contactless acquisition techniques present advantages which includes multiple acquisitions of the sample and do not alter the crime scene hance leaving room for further processing over destructive methods. Moreover, there are cases where traditional methods completely fail; such as acquiring fingerprints deposited on thin layers of plastic, fingerprints sandwiched between duct tapes.

* Supported by organization x.

Chromatic white light sensor, alternative light sources, infrared sensors and Optical coherence tomography (OCT) [10, 5, 3, 2] are some of the contactless acquisition methods. OCT is a system that uses light to capture a 3D representation of an object. The OCT system offers advantages of high-resolution, contactless and ability to penetrate few millimetres on the surface imaging.

In this work, OCT is used to acquire latent fingerprints from glass and stainless steel. However, OCT does present some technical challenges as a fingerprint sensor. The images that are produced by OCT are often immersed in speckle noise. Any unwanted modifications of a signal or image are called noise. Noise signal may appear as additive or multiplicative on an image [11, 10]. The linear filters may suppress additive noise signal while multiplicative is a bit complicated.

Speckle noise is a granular interference that inherently exists in and degrades the quality of the optical sensors images such as OCT. This type of noise is multiplicative; thus, linear filters such as median filter are unable to remove it. The methods that use wavelets are recommended for speckle noise removal [8, 14, 4, 12].

The process of removing noise from an image is called denoising. In this work a wavelet transform based denoising technique that uses stationary wavelet (SWT), β constant and mean is proposed. The method is implemented in an effort to remove speckle noise from the latent fingerprint images acquired using the OCT system. The proposed technique is compared to normalShrink and adaptive threshold [14]. Peak-to-signal-to-noise-ratio (PSNR), Signal-to-noise-ratio (SNR) and root mean square error (RMSE) are used as the quantitative measure 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 custom made spectral domain OCT system with the specifications on Table 1 was used.

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 [14]. The

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

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 the high vertical frequency (LH), sub-image with high horizontal frequency but the low vertical frequency (HL) and (HH) which has a 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 into four components (LL, HL, LH and HH) [14, 15].

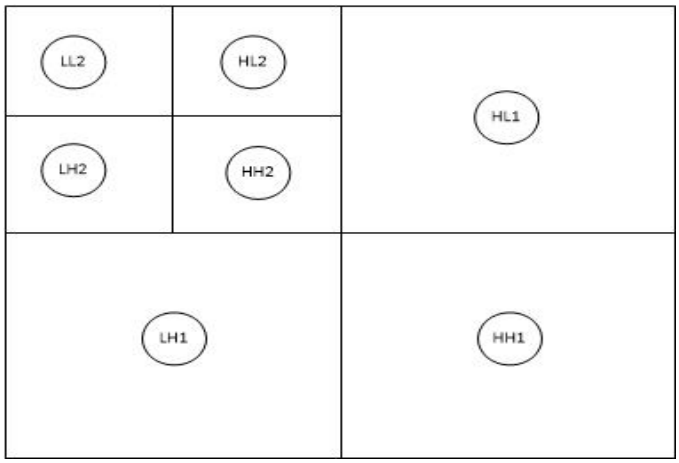


Fig. 1: Image wavelet decomposition.

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. 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, 13].

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

4 Wavelets Denoising Techniques

The following wavelets denoising techniques have been implemented in MATLAB for fingerprint images captured using the OCT system. The *bior2.6* wavelet filter is used for these techniques, and the decomposition level 1, 2, 3 and 4 are chosen.

In this work, adaptive histogram equalization was used as the pre-processing and post-processing technique. The PSNR, SNR and RMSE are used for quantitative quality measure metrics. The SNR is the measure used in science and engineering to compare the level of the desired signal to the level of background. The PSNR is the ratio between maximum possible power of a signal and the power of the corrupt signal. The RMSE is the square root of the cumulative squared error between the denoised and the original imag. The quantitative metrics are shown in Table 2.

Table 2: Quantitative metrics

Metric	Formula
RMSE	$\frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[(G(x,y)-F(x,y))^2]}{M \times N}$
SNR	$\frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}F(x,y)^2}{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[(G(x,y)-F(x,y))^2]}$
PSNR	$10log_{10}\left(\frac{R^2}{RMSE^2}\right)$

where $F(x, y)$ is the denoised image, $G(x, y)$ is the corrupted image and $R = 255$.

4.1 NormalShrink

NormalShrink technique is a wavelet domain denoising method based on the generalized Gaussian distribution(GGD) subband coefficients modelling [9]. The threshold value of NormalShrink is defined as

$$T = \beta \frac{\sigma^2}{\sigma_y}, \tag{3}$$

where σ^2 is noise variance estimated by (4):

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

The σ_y is the standard deviation of the noisy signal which is computed as

$$\sigma_y^2 = \frac{1}{M^2} \sum_{i=1}^{M} \sum_{j=1}^{M} I(i,j)^2, \tag{5}$$

where M is the number of pixels in image I. The β constant is the scale parameter which is computed as,

$$\beta = \sqrt{log\left(\frac{L_k}{J}\right)}, \tag{6}$$

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 [7].

4.2 Adaptive Threshold

The adaptive threshold proposed in [14] 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,

$$T = \begin{cases} \frac{\sigma^2_{W_\Phi}(i)}{\sigma_{W_F}(D,i)} & \text{if } \sigma_{W_F}(D,i) \neq 0 \\ max(W_{x,y}(D,i)) & \text{if } \sigma_{W_F}(D,i) = 0 \end{cases}, \tag{7}$$

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:

$$\sigma_{W_F}(D,i) = \sqrt{max(\sigma^2_{W_G}(D,i) - \sigma^2_{W_\Phi}(i), 0)} \tag{8}$$

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

$$\sigma_{W_\Phi} = \frac{median(|HH_i|)}{0.6745}, \tag{9}$$

and the image signal noise variance is given by:

$$\sigma^2_{W_G}(D,i) = \frac{1}{N(i)^2} \sum_{x=1}^{N(i)} \sum_{y=1}^{N(i)} W_G(D,i)^2, \tag{10}$$

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.

4.3 Proposed Method

The adaptive threshold [14] is modified using β constant from normalShrink and diagonal details are computed using the mean instead of median. The block diagram of the proposed method is shown in Fig. 2.

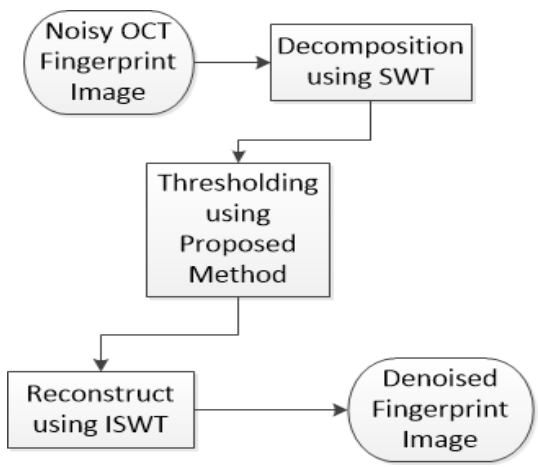


Fig. 2: The basic structure of wavelet transform based image denoising

The threshold value in (7) is multiplied by the constant β defined in (6), then the threshold value is computed as:

$$T = \begin{cases} \beta_i \left(\frac{\sigma^2_{W_\Phi}(i)}{\sigma_{W_F}(D,i)} \right) & \text{if } \sigma_{W_F}(D,i) \neq 0 \\ \beta_i(max(W_{x,y}(D,i))) & \text{if } \sigma_{W_F}(D,i) = 0 \end{cases}, \tag{11}$$

The mean is proposed to compute the variance on the HH subband instead of the traditional median given in (9)

$$\sigma_{W_\Phi} = \frac{mean(|HH_i|)}{0.6745}, \tag{12}$$

After calculating the noise variance, the new modified adaptive threshold is applied to OCT noisy latent fingerprint image and the procedure is outlined in algorithm 1.

Algorithm 1: The noisy fingerprint image is then denoised using the following procedure

Input: Noisy OCT latent fingerprint image.
Output: Denoised image.

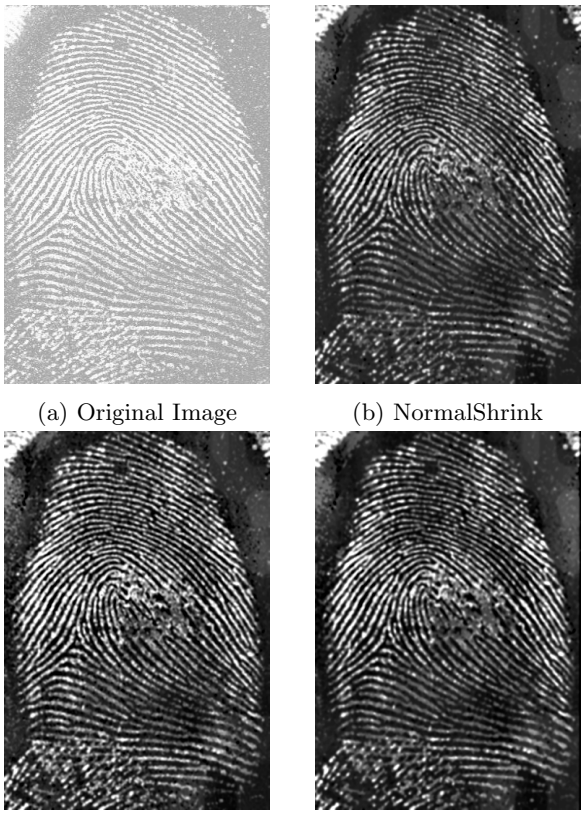
i. Decompose the noisy image using forward SWT.
   a. Estimate the noise signal standard deviation using (12).
   b. Calculate the variance ($\sigma^2_{W_G}(D,i)$) of the noisy image.
   c. Calculate the standard deviation ($\sigma_{W_F}(D,i)$) of the original image.
ii. Threshold the wavelet coefficients in detail subband using the proposed method.
iii. Reconstruct using inverse ISWT to get the denoised image.
iv. Evaluate the performance using image metrics quality measures (PSNR, SNR and MSE).

5 Experimental Results

The proposed method, normalShrink and adaptive threshold techniques were implemented in MATLAB. The images in Fig. 3, shows the experimental results of these techniques. Table 3 shows the quantitative performance of these denoising techniques.

Table 3: Shows the PSNR, SNR and RMSE value for each technique with *bior2.6* as a wavelet filter at decomposition level 1 to 4.

	PSNR	**SNR**	**RMSE**
Level 1			
NormalShrink	40.9527	**20.2523**	5.2217
Adaptive Threshold	40.9111	16.9878	5.2719
Proposed Method	**41.0494**	19.6588	**5.1066**
Level 2			
NormalShrink	40.9789	**19.6855**	5.1903
Adaptive Threshold	40.9111	16.9878	5.2719
Proposed Method	**41.0689**	18.9289	**5.0838**
Level 3			
NormalShrink	40.9903	**19.4738**	5.1767
Adaptive Threshold	40.9111	16.9878	5.2719
Proposed Method	**41.0312**	18.4767	**5.1282**
Level 4			
NormalShrink	**40.9928**	**19.2253**	**5.1737**
Adaptive Threshold	40.9111	16.9878	5.2719
Proposed Method	40.9701	18.0956	5.2008



(a) Original Image (b) NormalShrink

(c) Adaptive Threshold (d) Proposed Method

Fig. 3: (a) OCT noisy latent fingerprint (b) Donoised by NormalShrink, (c) Denoised by adaptive threshold, (d) Denoised by proposed method

6 Discussion

Latent fingerprint images were successfully acquired by the OCT system from glass, stainless steel and brass (doorknob). Fig. (3a) shows the latent fingerprint image acquired from stainless steel. Fig 3b, 3c and 3d shows the latent fingerprint image denoised by normalShrink, adaptive threshold and proposed method respectively.

The proposed method outperforms normalShrink and adaptive threshold in terms of PSNR and RMSE from level 1 to 3. At level 4 only normalShrink is optimal; however, it is not recommended to decompose image to higher levels as it may be distorted [14]. Therefore, techniques that produce good results at lower levels are often regarded as better solutions. The proposed method is better at level one up to three; thus, it outperforms the adaptive threshold and normalShrink method.

7 Conclusion and Future Work

A method to remove speckle noise present in OCT latent fingerprint images using SWT, β constant and mean is proposed in this paper. At the start, the OCT latent fingerprint image is decomposed using SWT into four different subbands. The proposed method is applied to the wavelets coefficients using soft thresholding. Lastly, the noise free image latent fingerprint image is reconstructed from the thresholded subbands using inverse SWT. The *bior2.6* wavelet filter gives good results for the proposed method from level 1 up to level 3. The proposed method outclass both normalShrink and adaptive threshold. In future, the proposed method will be tested using different wavelet filters such as haar, db2 and sym4.

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