FINGERPRINT IMAGE ENHANCEMENT USING STFT ANALYSIS

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Abstract

Contrary to popular belief, despite decades of research in fingerprints, reliable fingerprint recognition is an open problem. Extracting features out of poor quality prints is the most challening problem faced in this area. This paper introduces a new approach for fingerprint enhancement based on Short Time Fourier Transform(STFT) Analysis. STFT is a well known technique to analyze non-stationary signals. We extend its application to 2D images. The algorithm simultaneously estimates all the intrinsic properties of the fingerprints such as the foreground region mask, local ridge orientation and local frequency orientation. Furthermore we propose a probabilistic approach of robustly estimating these parameters. We compare the proposed approach to other filtering approaches and show that our technique performs favorably. We also objectively measure the improvement in recognition rate due to our enhancement. We obtain a 17% improvement in the recognition rate on a set of 800 images from the FVC2002 database.

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Fingerprint Image Enhancement Using STFT Analysis

1 Introduction

The performance of a fingerprint feature extraction and matching algorithm depend heavily upon the quality of the input fingerprint image. While the ’quality’ of a fingerprint image cannot be objectively measured, it roughly corresponds to the the clarity of the ridge structure in the fingerprint image. A ’good’ quality fingerprint image has high contrast and well defined ridges and valleys. A ’poor’ quality fingerprint is marked by low contrast and ill-defined boundaries between the ridges and valleys. The quality of fingerprint encountered during verification varies over a wide range as shown in Figure 1. It is estimated that roughly 10% of the fingerprint encountered during verification can be classified as ’poor’ [8]. Poor quality fingerprints lead to generation of spurious minutiae and loss of genuine minutiae, the net effect of both leading to loss in accuracy of the matcher.

The robustness of the recognition system can be improved by incorporating an enhancement stage prior to feature extraction. Due to the non-stationary nature of the fingerprint image, general-purpose image processing algorithms are not very useful in this regard but serve as a preprocessing step in the overall enhancement scheme. Furthermore pixel oriented enhancement schemes like histogram equalization [4], mean and variance normalization [6], weiner filtering [15] improve the legibility of the fingerprint but do not alter the ridge structure. Also, the definition of noise in a generic image and a finger print are widely different. The *noise* in a fingerprint image consists of breaks in the directional flow of ridges.

A single filter that operates on the entire image is not suitable due to the non-stationary nature of the fingerprint image. Instead, the filter parameters have to be adapted to enhance the local ridge structure. A majority of the techniques are based on the use of *contextual* filters whose parameters depend on the local ridge frequency and orientation. Due to the regularity and continuity properties of the fingerprint image, occluded and corrupted regions can be recovered using the contextual information from the surrounding neighborhood. The efficiency of an automated fingerprint enhancement algorithm depends on the extent to which they utilize contextual information.

The filters themselves may be defined in spatial or in the Fourier domain. O’Gorman et al. [9] proposed the use of contextual filters for fingerprint image enhancement for the first time. They used an anisotropic smoothening kernel whose major axis is oriented parallel to the ridges. Recently, Greenberg et al. [15] also proposed the use of an anistropic filter that is based on structure adaptive filtering by Yang et al. [20]. Another approach based on directional filtering kernel was given by Hong et al. [6]. The algorithm uses a properly oriented Gabor kernel for performing the enhancement. Gabor filters have important properties from a signal processing perspective such as optimal joint space frequency resolution [12]. This is by far, the most popular approach for fingerprint image enhancement. Other approaches based on spatial domain techniques can be found in [16]. More recent work based on reaction diffusion techniques can be found in [3, 19].

Sherlock and Monro [2] perform contextual filtering completely in the Fourier Domain. Here, each image is convovled with precomputed filters of the same size as the image. The precomputed filter bank are oriented in eight or sixteen different directions. However, the algorithm assumes that the ridge frequency is constant through out the image in order to prevent having a large number of precomputed filters. Therefore the algorithm does not utilize the full contextual information provided by the fingerprint image.

2 Proposed Approach

We present a new fingerprint image enhancement algorithm based on contextual filtering in the Fourier domain. The proposed algorithm is able to simultaneously estimate the local ridge orientation and ridge frequency information using short time Fourier Analysis. The algorithm is also able to successfully segment the fingerprint images.

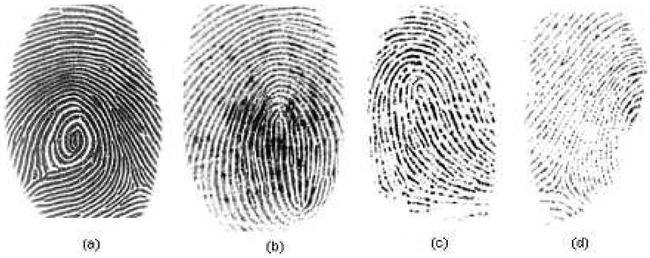


Figure 1: **Fingerprint images of different quality. The quality decreases from left to right. (a) Good quality image with high contrast between the ridges and valleys (b) Insufficient distinction between ridges and valleys in the center of the image (c) Dry print**

2.1 Short Time Fourier Analysis

The fingerprint image may be thought of as a system of oriented texture with the local ridge orientation and ridge frequency varying slowly through out the image. Due to this non-stationary nature of the image, traditional Fourier analysis is not adequate to analyze the image completely. We need to resolve the properties of the image both in space and also in frequency. We can extend the traditional one dimensional time-frequency analysis to two dimensional image signals to perform short (time/space)-frequency analysis. In this section we recapitulate some of the principles of 1D STFT analysis and show how it is extended to 2D for the sake of analyzing the fingerprint.

When analyzing a non-stationary 1D signal $x(t)$ it is assumed that it is approximately stationary in the span of a temporal window $w(t)$ with finite support. The STFT of $x(t)$ is now represented by time frequency *atoms* $X(\tau, \omega)$ [5] and is given by

$$X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)\omega^*(t-\tau)e^{-j\omega t}dt \tag{1}$$

In the case of 2D signals such as a fingerprint image, the space-frequency *atoms* is given by

$$X(\tau_1, \tau_2, \omega_1, \omega_2) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I(x,y)W^*(x-\tau_1, y-\tau_2)e^{-j(\omega_1 x+\omega_2 y)}dxdy \tag{2}$$

Here τ_1, τ_2 represent the spatial position of the two dimensional window W(x,y). ω_1, ω_2 represents the spatial frequency parameters. Unlike regular fourier transform, the result of the STFT is dependent on the choice of the window $w(t)$. For the sake of analysis any smooth spectral window such as hanning, hamming or even a gaussian [13] window may be utilized. However, since we are also interested in enhancing and reconstructing the fingerprint image directly from the fourier domain, our choice of window is fairly restricted. Figure 2 illustrates how the spectral window is parameterized. At each position of the window, it overlaps OVRLP pixels with the previous position. This preserves the ridge continuity and eliminates 'blocking' effects common with other block processing image operations. Each such analysis frame yields a single value of the dominant orientation and frequency in the region centered around (τ_1, τ_2). In order to provide suitable reconstruction during enhancement, we utilize a raised cosine window that tapers smoothly near the border and is unity at the center of the window. The raised cosine spectral window is obtained using

$$W(x,y) = \left\{ \begin{array}{c} 1 \text{ if}(|x|,|y|) < \text{BLKSZ}/2 \\ \frac{1}{2}(1+cos(\frac{\pi(x-BLKSZ/2)}{OVRLP})) \text{ otherwise} \end{array} \right\} (x,y) \in [-\frac{WNDSZ}{2}, \frac{WNDSZ}{2}) \tag{3}$$

With the exception of the singularities such as core and delta [8] any local region in the fingerprint image has a consistent orientation and frequency. Therefore, the local region can be modeled as a surface wave that is characterized completely by its orientation θ and frequency f. It is these parameters that we hope to infer by performing STFT analysis. This approximation model does not account for the presence of local discontinuities but is useful enough for our purpose. A local region of the image can be modeled as a surface wave according to

$$I(x,y) = A\left\{2\pi f \cos\left(x\cos(\theta) + y\sin(\theta)\right)\right\} \tag{4}$$

The parameters of the surface wave (f, θ) may be easily obtained from its Fourier spectrum that consists of two impulses whose distance from the origin indicates the frequency and its angular location indicates the orientation of the wave. However, this straight forward approach is not very useful since the maximum response is prone to errors. Creases running across the fingerprint can easily put off such maximal response estimators. Instead, we

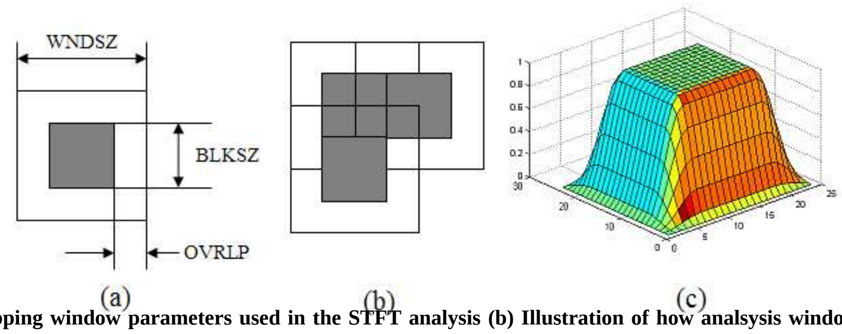


Figure 2: **(a)Overlapping window parameters used in the STFT analysis (b) Illustration of how analsysis windows are moved during analysis (b)Spectral window used during STFT analysis**

propose a proabilistic approximation of the dominant ridge orientation and frequency. It is to be noted that the surface wave model is only an approximation, and the Fourier spectrum of the real fingerprint images is characterized by a distribution of energies across all frequencies and orientations. We can represent the Fourier spectrum in polar form as $F(r,\theta)$. We can define a probability density function $p(r,\theta)$ and the marginal density functions $p(\theta)$, $p(r)$ as

$$p(r,\theta) = \frac{|F(r,\theta)|^2}{\int_r \int_\theta |F(r,\theta)|^2} \quad (5)$$

$$p(r) = \int_\theta p(r,\theta)d\theta, p(\theta) = \int_r p(r,\theta)dr \quad (6)$$

2.2 Ridge Orientation Image

We assume that the orientation θ is a random variable that has the probability density function $p(\theta)$. The expected value of the orientation may then be obtained by performing a vector averaging according to (Eqn. 7). The terms $\sin(2\theta)$ and $\cos(2\theta)$ are used to resolve the orientation ambiguity between orientations $\pm 180°$.

$$E\{\theta\} = \frac{1}{2}tan^{-1}\left\{\frac{\int_\theta p(\theta)\sin(2\theta)d\theta}{\int_\theta p(\theta)\cos(2\theta)d\theta}\right\} \quad (7)$$

The estimate is also optimal from a statistical sense as shown in [11]. However, if there is a crease in the fingerprints that spans several analysis frames, the orientation estimation will still be wrong. The estimate will also be inaccurate when the frame consists entirely of unrecoverable regions with poor ridge structure or poor ridge contrast. In such instances, we can estimate the ridge orientation by considering the orientation of its immediate neighborhood. Therefore, the resulting orientation image *O(x,y)* is further smoothened using vectorial averaging. The smoothened image *O'(x,y)* is obtained using

$$O'(x,y) = \frac{1}{2}tan^{-1}\left\{\frac{\sin(2O(x,y)) * W(x,y)}{\cos(2O(x,y) * W(x,y)}\right\} \quad (8)$$

Here W(x,y) represent a gaussian smoothening kernel. It has been our experience that a smoothening kernel of size 3x3 applied repeatedly provides a better smoothening result than using a larger kernel of size 5x5 or 7x7.

2.3 Ridge Frequency Image

The average ridge frequency is estimated in a manner similar to the ridge orientation. We can assume the ridge frequency to be a random variable with the probability density function $p(r)$ as in (Eqn. 6). The expected value of the ridge frequency is given by

$$E\{r\} = \int_r p(r)rdr \quad (9)$$

The frequency map so obtained is smoothened by process of isotropic diffusion. Simple smoothening cannot be applied since the ridge frequency is not defined in the background regions. Furthermore the ridge frequency estimation

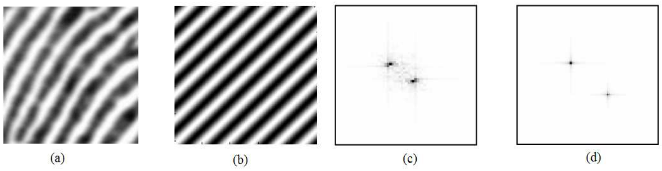


Figure 3: **(a) Local region in a fingerprint image (b) Surface wave approximation (c,d) Fourier spectrum of the real fingerprint and the surface wave. The symmetric nature of the Fourier spectrum arrives from the properties of the Fourier transform for real signals [4]**

obtained at the boundaries of the fingeprint foreground and the image background is inaccurate in practice. The errors in this region will propagate as a result of the plain smoothening. The smoothened is obtained by the following.

$$F'(x,y) = \frac{\sum_{u=x-1}^{x+1} \sum_{v=y-1}^{y+1} F(u,v)W(u,v)I(u,v)}{\sum_{v=y-1}^{y+1} W(u,v)I(u,v)} \tag{10}$$

This is similar to the approach proposed in [6]. Here W(x,y) represents a gaussian smoothening kernel of size 3x3. The indicator variable I(x,y) ensures that only valid ridge frequencies are considered during the smoothening process. I(x,y) is non zero only if the ridge frequency is within the valid range. It has been observed that the inter-ridge distance varies in the range of 3-25 pixels per ridge [6]. Regions where inter-ride separation/frequency are estimated to be outside this range are assumed to be invalid.

2.4 Region Mask

The fingerprint image may be easily segmented based on the observation that the surface wave model does not hold in regions where ridges do not exist. In the areas of background and noisy regions, there is very little structure and hence very little energy content in the Fourier spectrum. We define an energy image E(x,y), where each value indicates the energy content of the corresponding block. The fingerprint region may be differentiated from the background by thresholding the energy image. We take the logarithm values of the energy to reduce the large dynamic range to a linear scale.

$$E(x,y) = \log \left\{ \int_r \int_\theta |F(r,\theta)|^2 \right\} \tag{11}$$

The region mask is obtained by thresholding . We use Otsu's optimal thresholding [10] technique to automatically determine the threshold. The resulting binary image is processed further to retain the largest connected component and binary morphological processing [17].

2.4.1 Coherence Image

Block processing approaches are associated with spurious artifacts caused by discontinuities in the ridge flow at the block boundaries. This is especially problematic in regions of high curvature close to the core and deltas that have more than one dominant direction. These problems are clearly illustrated in [**?**]. We rely on the flow-orientation/angular coherence measure [14] to estimate the angular bandwidth required to enhance such regions.

$$C(x_0,y_0) = \frac{\sum_{(i,j)\in W} |cos\left(\theta(x_0,y_0) - \theta(x_i,y_i)\right)|}{WxW} \tag{12}$$

The coherence is high when the orientation of the central block $\theta(x_0,y_0)$ is similar to each of its neighbors $\theta(x_i,x_j)$. In a fingerprint image, the coherence is expected to be low close to the points of the singularity. In our enhancement scheme, we increase the angular bandwidth in regions of low coherence and thus prevent spurious artifacts in such regions.

3 Experimental Evaluation

The algorithm for enahncement can be outlined as follows:The algorithm consists of two stages. The first stage consists of STFT analysis and the second stages performs the contextual filtering. The STFT stage yields the ridge orientation

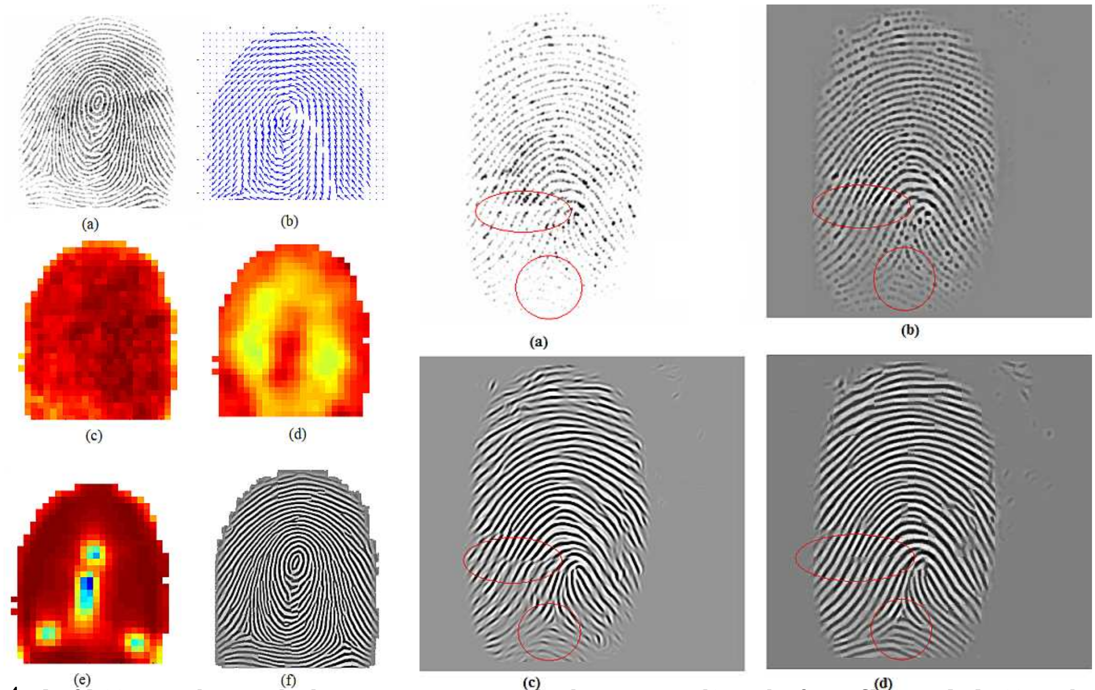


Figure 4: **[Left] (a)Original image displaying poor contrast and ridge structure (b)Result of root filtering [18]. (c)Result of Gabor filter based enhancement (d) Result using proposed algorithm .[Right] (a)Original Image (b)Orientation Image (c)Energy Image (d)Ridge Frequency Image (e)Angular Coherence Image (f)Enhanced Image**

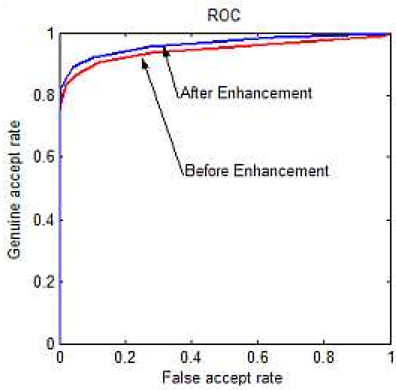
image, ridge frequency image and the block energy image which is then used to compute the region mask. Therefore the analysis phase simultaneously yields all the intrinsic images that are needed to perform full contextual filtering. The filter itself is separable in angular and frequency domains and is identical to the filters mentioned in [2].

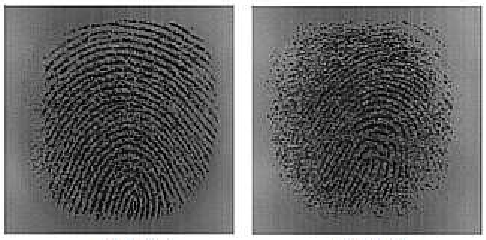
The results of each stage of the STFT analysis and the enhancement is shown in Figure 4. It can be seen that the quality of reconstruction is not affected even around the points of high curvature marked by the presence of the singularities. Figure 4 shows the comparative results for a poor quality fingerprint image. It can be seen from the result that the proposed approach performs better than the root filtering [18] and the Gabor filter based approach. We used Peter Kovesi's implementation [7] of Hong et. al's [6] paper for this purpose. The better performance of the proposed approach can be attributed to the simultaneous computation of the intrinsic images using STFT analysis. While in the Gabor filter based approach errors in orientation estimation also propagate to ridge frequency estimation leading to imperfect reconstruction.

While the effect of the enhancement algorithm may be guaged visually, the final objective of the enhancement process is to increase the accuracy of the recognition system. We evaluate the effect of our enhancement on a set of 800 images (100 users, 8 images each) derived from FVC2002 [1] DB3 database. The total number of genuine and impostor comparision are 2800 and 4950 respectively. We used NIST's NFIS2 open source software (http://fingerprint.nist.gov) for the sake of feature extraction and matching. The ROC curves before and after enhancement are as shown in the Figure 5. It can be seen that there is a net improvement of 17% on the recognition rate.

4 Summary

The performance of a fingerprint feature extraction and matching algorithms depend heavily upon the quality of the input fingerprint image. We have presented a new fingerprint image enhancement algorithm based on STFT analysis and contextual/non-stationary filtering in the Fourier domain. The algorithm has several advantages over the techniques found in literature such as (i) All the instrinsic images(ridge orientation,ridge frequency, region mask) are estimated simultaneously from STFT analysis. This prevents errors in ridge orientation estimation from propagating to other stages. Furthermore, the estimation is probabilistic and is therefore more robust.(ii)The enhancement utilizes the full contextual information(orientation,frequency,angular coherence) for enhancement. (iii) The algorithm has reduced space requirements compared to more popular Fourier domain based filtering techniques. We perform





DB3 Results	Equal Error Rate
Without Enhancement	10.35%
With Enhancement	8.5%
Improvement	17%

(a) (b)

Figure 5: **(a)ROC curves with and without enhancement (b)Some sample images from DB3 database and the effect of enhancement on the overall accuracy of the system**

an objective evaluation of the enhancement algorithm by considering the improvement in matching accuracy for poor quality prints. We show that it results in 17% improvement in recognition rate over a set of 800 images in FVC2002 DB3 [1] database. Our future work includes developing a more robust orientation smoothening algorithm prior to enhancement. The matlab code for the enhancement is available for download at www.cubs.buffalo.edu and at http://www.mathworks.com/matlabcentral/.

References

[1] Fingerprint verification competition. http://bias.csr.unibo.it/fvc2002/.

[2] B.G.Sherlock, D.M.Monro, and K.Millard. Fingerprint enhancement by directional fourier filtering. In *Visual Image Signal Processing*, volume 141, pages 87–94, 1994.

[3] Oriented Texture Completion by AM-FM Reaction-Diffusion. *IEEE Transactions on Image Processing*, 10(6), 2001.

[4] Gonzalez, Woods, and Eddins. *Digital Image Processing*. Prentice Hall, 2004.

[5] S. Haykin and B. V. Veen. *Signals and Systems*. John Wiley and Sons, 1999.

[6] L. Hong, Y. Wang, and A. K. Jain. Fingerprint image enhancement: Algorithm and performance evaluation. *Transactions on PAMI*, 21(4):777–789, August 1998.

[7] P. D. Kovesi. Matlab functions for computer vision and image analysis. http://www.csse.uwa.edu.au/simpk/research/matlabfns.

[8] D. Maio, D. Maltoni, A. K. Jain, and S. Prabhakar. *Handbook of Fingerprint Recognition*. Springer Verlag, 2003.

[9] L. O'Gormann and J.V.Nickerson. An approach to fingerprint filter design. *Pattern Recognition*, 22(1):29–38, 1989.

[10] N. Otsu. A threshold selection method from gray level histograms. *IEEE Transactions on Systems, Man and Cybernetics*, 9:62–66, 1979.

[11] Papoulis and Pillai. *Probability, Random Variables and Stochastic processes*. Mc Graw Hill, 2002. 4th edition.

[12] Shie Qian and Dapang Chen. *Joint Time-Frequency Analysis, Methods and Applications*. Prentice Hall, 1996.

[13] Rabiner and Schafer. *Digital Processing of Speech Signals*. Prentice Hall International, 1978.

[14] A. Ravishankar Rao. *A Taxonomy of Texture Descriptions*. Springer Verlag.

[15] Greenberg S., Aladjem M., Kogan D., and Dimitrov I. Fingerprint image enhancement using filtering techniques. In *International Conference on Pattern Recognition*, volume 3, pages 326–329, 2000.

[16] A. Sherstinsky and R. W. Picard. Restoration and enhancement of fingeprint images using m-lattice, 1994.

[17] Sonka, Hlavac, and Boyle. *Image Processing, Analysis and Machine Vision, second edition*. Thomson Asia, 2004.

[18] C. I. Watson, G. T. Candela, and P. J. Grother. Comparison of fft fingerprint filtering methods for neural network classification. *NISTIR*, 5493, 1994.

[19] Che-Yen Wen and Chiu-Chung Yu. Fingerprint enhancement using am-fm reaction diffusion systems. *Journal of Forensic Science*, 48(5), 2003.

[20] G. Z. Yang, P. Burger, D. N. Firmin, and S. R. Underwood. Structure adaptive anisotropic image filtering. *Image and Vision Computing*, 14:135–145, 1996.