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Fingerprint Image Enhancement Using STFT Analysis

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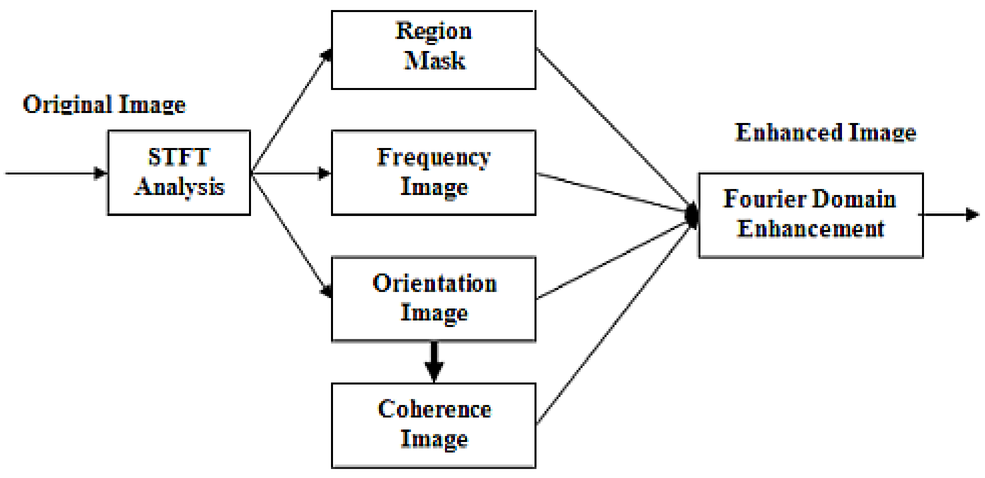
Abstract: *The performance of a fingerprint feature extraction and matching algorithm depend heavily upon the quality of the input fingerprint image. While the 'quality' of a fingerprint image cannot be objectively measured, it roughly corresponds to the the clarity of the ridge structure in the fingerprint 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. There are several reasons that may degrade the quality of the fingerprint image.*
1. The ridges are broken by presence of creases, bruises or wounds on the fingerprint surface
2. Excessively dry fingers lead to fragmented ridges
3. Sweaty fingerprints lead to bridging between successive ridges
The quality of fingerprint encountered during verification varies over a wide range .It is estimated that roughly 10% of the fingerprint encountered during verification can be classified as 'poor' . Poor quality fingerprints lead to generation of spurious minutiae. In smudgy regions, genuine minutiae may also be lost, 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 pre processing step in the overall enhancement scheme. Furthermore pixel oriented enhancement schemes like histogram equalization , mean and variance normalization , weiner filtering 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. In the next section, we will discuss some filtering approaches that were specifically designed to enhance the ridge structure.

I. Introduction



II. Spatial Domain Filtering

O'Gorman et al. 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. For efficiency, they pre compute the filter in 16 directions. The net result of the filter is that it increases contrast in a direction perpendicular to the ridges while performing smoothening in the direction of the ridges. Recently, Greenberg et al. proposed the use of an anisotropic filter that is based on structure adaptive filtering [95]. The filter kernel is adapted at each point in the image and is given by

$$f(x, x_0) = S + V\rho(x - x0)exp\left\{-\left(\frac{((x - x_0).n)^2}{\sigma_1^2(x_0)} + \frac{((x - x_0).n_\perp)^2}{\sigma_2^2(x_0)}\right)\right\}$$

Here *n* and *n⊥* represents unit vectors parallel and perpendicular to the ridges respectively. $\sigma 1$ and $\sigma 2$ control the eccentricity of the filter. $\rho(x - x0)$ determines the support of the filter and chosen such that $\rho(x) = 0$ when $|x - x0| > r$.

The main stages of their algorithm are as follows

1. Normalization: This procedure normalizes the global statistics of the image, by reducing each image to a fixed mean and variance. Although this pixel wise operation does not change the ridge structure, the contrast and brightness of the image are normalized as a result. The normalized image is defined as

$$G(i,j) = \left\{ \begin{array}{c} M_0 + \sqrt{\frac{VAR_0((I-M)^2)}{VAR}}, \text{if } I(i,j) > M \\ M_0 - \sqrt{\frac{VAR_0((I-M)^2)}{VAR}}, \text{otherwise} \end{array} \right\}$$

2. Orientation Estimation: This step determines the dominant direction of the ridges in different parts of the fingerprint image . This is a critical process and errors occurring at this stage is propagated into the frequency estimation and filtering stages.
3. Frequency Estimation: This step is used to estimate the inter-ridge separation in different regions of the fingerprint image.
4. Segmentation: In this step, a region mask is derived that distinguishes between 'recoverable', 'unrecoverable' and 'background' portions of the fingerprint image.
5. Filtering: Finally using the context information consisting of the dominant ridge orientation and ridge separation, a band pass filter is used to enhance the ridge structure.

The algorithm uses a properly oriented Gabor kernel for performing the enhancement. Gabor filters have important signal properties such as optimal joint space frequency resolution . Daugman and Lee have used Gabor elementary functions as wavelet basis functions to represent generic 2D images. Daugman gives the following form for the 2D Gabor elementary function

$$G(x,y) = exp(-\pi[(x - x_0)^2\alpha^2 + (y - y_0)^2\beta^2]).exp(-2\pi\ i[u_0(x - x_0) + v_0(y - y_0)])$$

$x0$ and $y0$ represent the center of the elementary function in the spatial domain. $u0$ and $v0$ represent the modulation frequencies. $\alpha 2$ and $\beta 2$ represent the variance along the major and minor axes respectively and therefore the extent of support in the spatial domain. The even symmetric form that is oriented at an angle φ is given by

$$G(x,y) = exp\left\{-\frac{1}{2}\left[\frac{(x\cos(\phi))^2}{\delta_x^2} + \frac{(y\sin(\phi))^2}{\delta_y^2}\right]\right\}cos(2\pi f x\cos(\phi))$$

Here *f* represents the ridge frequency, φ represents the dominant ridge direction and the choice of $\delta 2x$ and $\delta 2y$ determines the shape of the envelope and also the trade of between enhancement and spurious artifacts . If $\delta 2x >> \delta 2y$ results in excessive smoothening in the direction of the ridges causing discontinuities and artifacts at the boundaries. Gabor elementary functions form a very intuitive representation of fingerprint images since they capture the periodic, non-stationary nature of the fingerprint regions. However, unlike fourier bases or discrete cosine bases, using Gabor elementary functions have the following problems.

1. From a signal processing point of view, they do not form a tight frame. This means that the image cannot be represented as a linear superposition of the Gabor elementary functions with coefficients derived by projecting the image onto the same set of basis functions. However, has derived conditions under which a set of self similar Gabor basis functions form a complete and approximately orthonormal set of basis functions.
2. They are biorthogonal bases. This means that the basis functions used to derive the coefficients (analysis functions) and the basis functions used to reconstruct the image (synthesis functions) are not identical or orthogonal to each other. However, Daugman proposes a simple optimization approach to obtain the coefficients.

3. From the point of enhancing fingerprint images also, there is no rigorously justifiable reason for choosing the Gabor kernel over other directionally selective filters such as directional derivatives of gaussians or steerable wedge filters. While the compact support of the Gabor kernel is beneficial from a time-frequency analysis perspective, it does not necessarily translate to an efficient means for enhancement. Our algorithm is based on a filter that has separable radial and angular components and is tuned specifically to the distribution of orientation and frequencies in the local region of the fingerprint image.

III. Fourier Domain Filtering

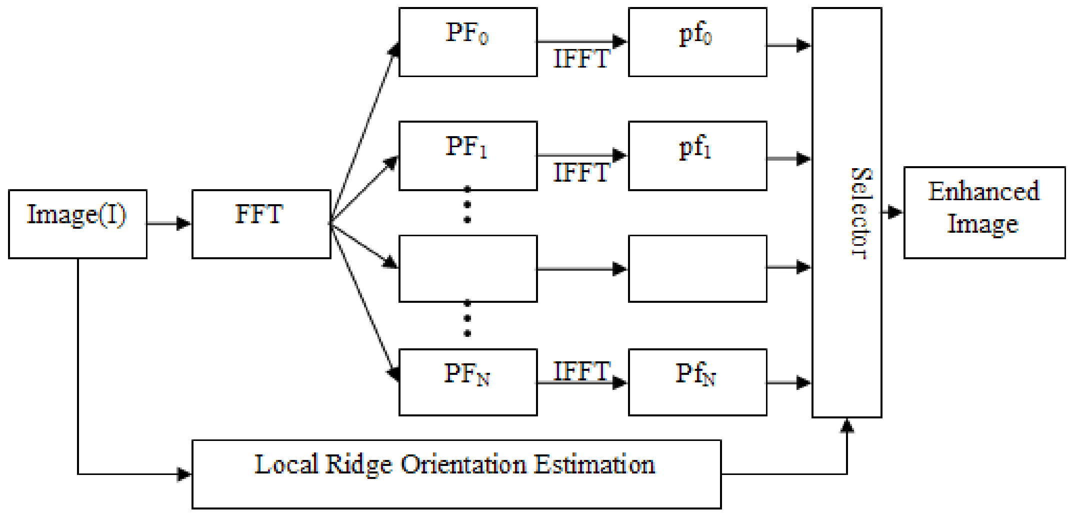
Although spatial convolution using anisotropic or gabor filters is easily accomplished in the Fourier domain, this section deals with filters that are defined explicitly in the Fourier domain. Sherlock and Monro [11] perform contextual filtering completely in the Fourier Domain. Each image is convolved with precomputed filters of the same size as the image. The precomputed filter bank (labeled PF0,PF1..PFN in Figure 2.4) are oriented in eight different direction in intervals of 45◦.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. The filter used is separable in radial and angular domain and is given by

$$
\begin{aligned}
H(\rho,\phi) &= H_\rho(\rho)H_\phi(\phi) \\
H_\rho(\rho) &= \sqrt{\left[\frac{(\rho\rho_{BW})^{2n}}{(\rho\rho_{BW})^{2n}+(\rho^2-\rho_0^2)^{2n}}\right]} \\
H_\phi(\phi) &= \left\{\begin{array}{c} \cos^2\frac{\pi}{2}\frac{(\phi-\phi_c)}{\phi_{BW}}\mathrm{if}|\phi|<\phi_{BW} \\ 0\mathrm{otherwise} \end{array}\right\}
\end{aligned}
$$

Here $H\rho(\rho)$ is a band-pass butterworth filter with center defined by $\rho 0$ and bandwidth ρBW.

The angular filter is a raised cosine filter in the angular domain with support φBW and center φc. However, the pre computed filters mentioned before are location independent. The contextual filtering is actually accomplished at the stage labeled 'selector'. The 'selector' uses the local orientation information to combine the results of the filter bank using appropriate weights for each output. The algorithm also accounts for the curvature of the ridges, something that was overlooked by the previous filtering approaches including gabor filtering. In regions of high curvature, having a fixed angular bandwidth lead to processing artifacts and subsequently spurious minutiae. In the approach proposed by Sherlock et al. the angular bandwidth of the filter is taken as a piece wise linear function of the distance from the singular points such as core and delta. However, this requires that the singular point be estimated accurately.

During STFT analysis, the image is divided into overlapping windows. It is assumed that the image is stationary within this small window and can be modeled approximately as a surface wave. The fourier spectrum of this small region is analyzed and probabilistic estimates of the ridge frequency and ridge orientation are obtained. The STFT analysis also results in an energy map that may be used as a region mask to distinguish between the fingerprint and the background regions. Thus, the STFT analysis results in the simultaneous computation of the ridge orientation image, ridge frequency image and also the region mask. The orientation image is then used to compute the angular coherence . The coherence image is used to adapt the angular bandwidth. The resulting contextual information is used to filter each window in the fourier domain. The enhanced image is obtained by tiling the result of each analysis window. It is assumed that the image is stationary within this small window and can be modeled approximately as a surface wave. The fourier spectrum of this small region is analyzed and probabilistic estimates of the ridge frequency and ridge orientation are obtained. The STFT analysis also results in an energy map that may be used as a region mask to distinguish between the fingerprint and the background regions. Thus, the STFT analysis results in the simultaneous computation of the ridge orientation image, ridge frequency image and also the region mask. The orientation image is then used to compute the angular coherence . The coherence image is used to adapt the angular bandwidth. The resulting contextual information is used to filter each window in the fourier domain. The enhanced image is obtained by tiling the result of each analysis window.



Short Time Fourier Analysis

The fingerprint image may be thought of as a system of oriented texture with non-stationary properties. Therefore 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* $X(\tau,\omega)$ [33] and is given by

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

Here $\tau1$, $\tau2$ represent the spatial position of the two dimensional window W(x,y). $\omega1$, $\omega2$ represents the spatial frequency parameters. Figure 2.7 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 'block' 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 ($\tau1$, $\tau2$). 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 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. 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

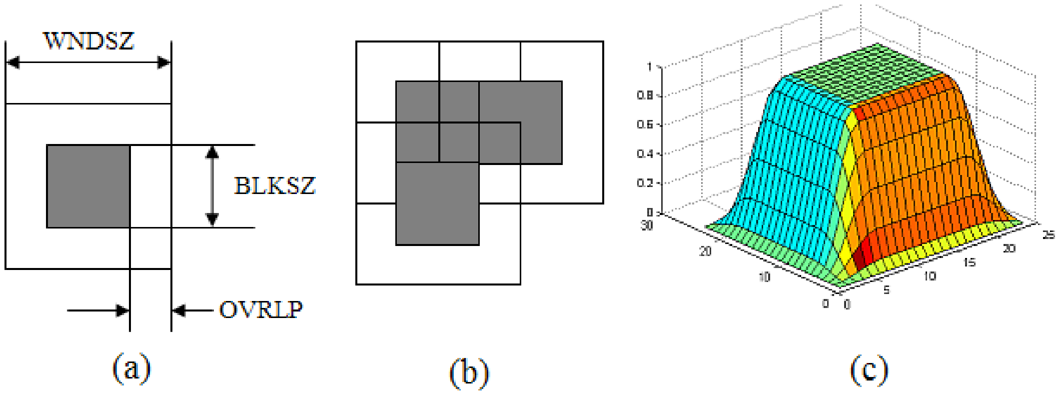
$$W(x,y) = \left\{ \begin{array}{c} 1 \text{ if}(|x|,|y|) < \text{BLKSZ}/2 \\ \frac{1}{2}(1+cos(\frac{\pi x}{OVRLP})) \text{ otherwise} \end{array} \right\} (x,y) \in [-WNDSZ/2, WNDSZ/2)$$

With the exception of the singularities such as core and delta, 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

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

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

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



(a)Overlapping window parameters used in the STFT analysis (b) Illustration of how analsys is windows are moved during analysis (b)Spectral window used during STFT analysis

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 propose a probabilistic 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

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

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

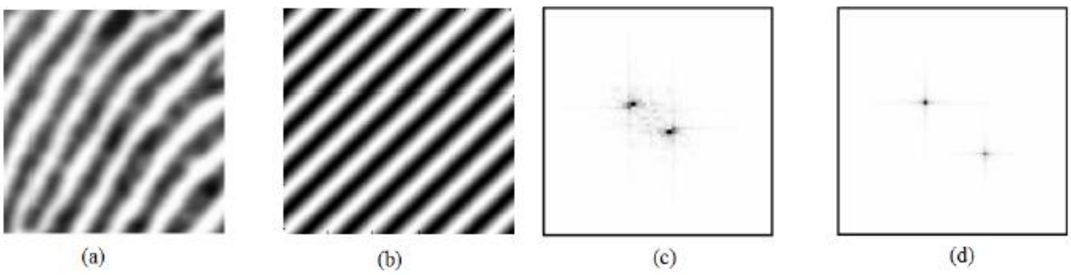


Figure 2.8: **Surface wave approximation: (a) Local region in a fingerprint image (b) Surface wave approximation (c,d) Fourier spectrum of the real fingerprint and the surface wave. The symmetric nature of the Fourier spectrum arrives from the properties of the Fourier transform for real signals**

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 Equation 2.21. The terms $\sin(2\theta)$ and $\cos(2\theta)$ are used to resolve the orientation ambiguity as mentioned before

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

The estimate is also optimal from a statistical sense as shown in [63]. 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 neighbourhood. The resulting orientation image *O(x, y)* is further smoothened using vectorial averaging. The smoothened image *O'(x, y)* is obtained using

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

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

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. The expected value of the ridge frequency is given by

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

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

This is similar to the approach proposed in [35]. Here H,W represent the height and width of the frequency image. 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 [35]. Regions where interride separation/frequency are estimated to be outside this range are assumed to be invalid.

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 [20]. 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 the large dynamic range to a linear scale.

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

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

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 . Sherlock and Monro used as piece-wise linear dependence between the angular bandwidth and the distance from the singular point location. However, this requires a reasonable estimation of the singular point location. Most algorithms for singular point location are obtained from the orientation [86, 8] map that is noisy in poor quality images. Instead we rely on the flow-orientation/angular coherence measure [73] that is more robust than singular point detection. The coherence is related to dispersion measure of circular data.

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

The coherence is high when the orientation of the central block $\theta(x0, y0)$ is similar to each of its neighbors $\theta(xi, xj)$. In a fingerprint image, the coherence is expected to be low close to the points of the singularity. In our enhancement scheme, we utilize this coherence measure to adapt the angular bandwidth of the directional filter.

Enhancement

The algorithm for enhancement can now be outlined as follows The algorithm consists of two stages.

```
Algorithm:  FFTEnhance
Inputs   :  Image I(x,y)
Outputs  :  Enhanced Image I'(x,y), Ridge Orientation Image O(x,y),
            Ridge Frequency Image F(x,y), Energy Image E(x,y),
            Orientation Coherence Image C(x,y), Region Mask(x,y)
STAGE I: STFT Analysis
1. For each overlapping block B(x,y) in the image
     a. Remove DC content of B, B=B-avg(B)
     b. Multiply by spectral window W
     c. Obtain the FFT of the block, F = FFT(B)
     d. Perform root filtering on F
     e. Perform STFT Analysis. The analysis yields values of
        E(x,y),O(x,y),F(x,y)
   end for
2. Smoothen orientation map O(x,y) by vector averaging to yield O'(x,y)
3. Perform isotropic diffusion on frequency map F(x,y) to yield F'(x,y)
4. Compute coherence image C(x,y) using O'(x,y)
5. Compute region mask R(x,y) by thresholding E(x,y)

STAGE II: Enhancement
6. For each overlapping block B(x,y) in the image
     a. Compute angular filter F_A centered around O(x,y) and with
        bandwidth inversely proportional to C(x,y)
     b. Compute radial filter F_R centered around frequency F(x,y).
     c. Filter the block in the FFT domain, F= F*F_R*F_A
     d. Compute the enhanced block B'(x,y) = IFFT(F)
   end for
7. Reconstruct the enhanced image by composing enhanced blocks B'(x,y)
```

Figure 2.9: **Outline of the enhancement algorithm**

The first stage consists of STFT analysis and the second stages performs the contextual filtering.

The STFT stage yields the ridge orientation 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

IV. Conclusion

The performance of a fingerprint feature extraction and matching algorithms depend heavily upon the quality of the input fingerprint image. We 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 proposed in literature such as (i) All the intrinsic 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 an objective evaluation of the enhancement algorithm by considering the improvement in matching accuracy for poor quality prints.