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Improved Technique for Fingerprint Segmentation

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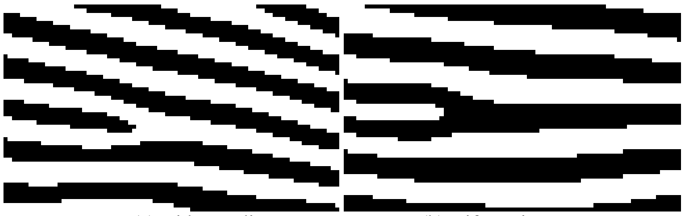
Abstract: The primary focus of the work in this paper is on the enhancement of fingerprint images, and the subsequent extraction of minutiae. Firstly, I have implemented a series of techniques for fingerprint image enhancement to facilitate the extraction of minutiae. Experiments were then conducted using a combination of both synthetic test images and real fingerprint images in order to provide a well-balanced evaluation on the performance of the implemented algorithm. The use of synthetic images has provided a more quantitative and accurate measure of the performance. Whereas real images rely on qualitative measures of inspection, but can provide a more realistic evaluation as they provide a natural representation of fingerprint imperfections such as noise and corrupted elements. Overall, I have implemented a set of reliable techniques for fingerprint image enhancement and minutiae extraction. These techniques can then be used to facilitate the further study of the statistics of fingerprints. In addition, these techniques can be also employed in other fingerprinting applications such as fingerprint matching and classification.

Keywords: Normalization, Orientation estimation, Ridge frequency estimation, Gabor filtering, Segmentation, Binarisation, Thinning.

I. INTRODUCTION

Fingerprints have been used for over a century and are the most widely used form of biometric identification. Fingerprint identification is commonly employed in forensic science to support criminal investigations, and in biometric systems such as civilian and commercial identification devices. Despite this widespread use of fingerprints, there has been little statistical work done on the uniqueness of fingerprint minutiae. In particular, the issue of how many minutiae points should be used for matching a fingerprint is unresolved. The fingerprint of an individual is unique and remains unchanged over a lifetime. A fingerprint is formed from an impression of the pattern of ridges on a finger. A ridge is defined as a single curved segment, and a valley is the region between two adjacent ridges. The minutiae, which are the local discontinuities in the ridge flow pattern, provide the features that are used for identification. Details such as the type, orientation, and location of minutiae are taken into account when performing minutiae extraction [9]. Galton [5] defined a set of features for fingerprint identification, which since then, has been refined to include additional types of fingerprint features. How-ever, most of these features are not commonly used in fingerprint identification systems. Instead the set of minutiae types are restricted into only two types, ridge endings and bifurcations, as other types of minutiae can be expressed in terms of these two feature types. Ridge endings are the points where the ridge curve terminates, and bifurcations are where a ridge splits from a single path to two paths at a Y-junction. occur due to variations in skin and impression conditions such as scars, humidity, dirt, and non-uniform contact with the fingerprint capture device [9]. Thus, image enhancement techniques are often employed to reduce the noise and enhance the definition of ridges against valleys.



(a) Ridge ending (b) Bifurcation

Figure 1.1: Example of a ridge ending and a bifurcation.

II. LITERATURE REVIEW

One of the most widely cited fingerprint enhancement techniques is the method employed by Hong et al. [8], which is based on the convolution of the image with Gabor filters tuned to the local ridge orientation and ridge frequency. The main stages of this algorithm include normalization, ridge orientation estimation, ridge frequency estimation and filtering. The first step in this approach involves the normalization of the fingerprint image so that it has a pre specified mean and variance. Due to imperfections in the fingerprint image capture process such as non-uniform ink intensity or non-uniform contact with the fingerprint capture device, a fingerprint image may exhibit distorted levels of variation in grey-level values along the ridges and valleys. Thus, normalization is used to reduce the effect of these variations, which facilitates the subsequent image enhancement steps.An orientation image is then calculated, which is a matrix of direction vectors representing the ridge orientation at each location in the image. The widely employed gradient-based approach is used to calculate the gradient [18, 20, 22], which makes use of the fact that the orientation vector is orthogonal to the gradient. Firstly, the image is partitioned into square blocks and the gradient is calculated for every pixel, in the x and y directions. The orientation vector for each block can then be derived by performing an averaging operation on all the vectors orthogonal to the gradient pixels in the block. Due to the presence of noise and corrupted elements in the image, the ridge orientation may not always be correctly determined. Given that the ridge orientation varies slowly in a local neighborhood, the orientation image is then smoothed using a low-pass filter to reduce the effect of outliers. The next step in the image enhancement process is the estimation of the ridge frequency image. The frequency image defines the local frequency of the ridges contained in the fingerprint. Firstly, the image is divided into square blocks and an oriented window is calculated for each block. For each block, an x-signature signal is constructed using the ridges and valleys in the oriented window. The x-signature is the projection of all the grey level values in the oriented window along a direction orthogonal to the ridge orientation. Consequently, the projection forms a sinusoidal-shape wave in which the centre of a ridge maps itself as a local minimum in the projected wave. The distance between consecutive peaks in the x-signature can then be used to estimate the frequency of the ridges.Fingerprint enhancement methods based on the Gabor filter have been widely used to facilitate various fingerprint applications such as fingerprint matching [17, 19] and fingerprint classification [12]. Gabor filters are bandpass filters that have both frequency-selective and orientation-selective properties [4], which means the filters can be effectively tuned to specific frequency and orientation values. One useful characteristic of fingerprints is that they are known to have well defined lo-cal ridge orientation and ridge frequency. Therefore, the enhancement algorithm takes advantage of this regularity of spatial structure by applying Gabor filters that are tuned to match the local ridge orientation and frequency. Based on the local orientation and ridge frequency around each pixel, the Gabor filter is applied to each pixel location in the image. The effect is that the filter enhances the ridges oriented in the direction of the local orientation, and decreases anything oriented differently. Hence, the filter increases the contras between the foreground ridges and the background, whilst effectively reducing noise. An alternative approach to enhancing the features in a fingerprint image is the technique employed by Sherlock [21] called directional Fourier filtering. The previous approach was a spatial domain technique that involves spatial convolution of the image with filters, which can be computationally expensive. Alternatively, operating in the frequency domain allows one to efficiently convolve the finger-print image with filters of full image size.The image enhancement process begins by firstly computing the orientation image. In contrast to the previous method, which estimates the ridge orientation using a continuous range of directions, this method uses a set of only 16 directions to calculate the orientation.

An image window is centered at a point in the raw image, which is used to obtain a projection of the local ridge information. The image window is then rotated in each of the 16 equally spaced directions, and in each direction a projection along the window's *y* axis is formed. The projection with the maximum variance is used as the dominant orientation for that point in the image. This process is then repeated for each pixel to form the orientation image. Similar to the filtering stage applied by Hong et. al.: after the orientation image has been computed, the raw image is then filtered using a set of bandpass filters tuned to match the ridge orientation. The image is firstly converted from the spatial domain into the frequency domain by application of the two-dimensional discrete Fourier transform. The Fourier image is then filtered using a set of 16 Butterworth filters with each filter tuned to a particular orientation. The number of directional filters corresponds to the set of directions used to calculate the orientation image. After each directional filter has been independently applied to the Fourier image, the inverse Fourier transform is used to convert each image back to the spatial domain, thereby producing a set of directionally filtered images called prefiltered images. The next step in the enhancement process is to construct the final filtered image using the pixel values from the prefiltered images. This requires the value of the ridge orientation at each pixel in the raw image and the filtering direction of each prefiltered image. Each point in the final image is then computed by selecting, from the prefiltered images the pixel value whose filtering direction most closely matches the actual ridge orientation. The output of the filtering stage is an enhanced version of the image that has been smoothed in the direction of the ridges. Lastly, local adaptive thresholding is applied to the directionally filtered image, which produces the final enhanced binary image. This involves calculating the average of the grey-level values within an image window at each pixel, and if the average is greater than the threshold, then the pixel value is set to a binary value of one; otherwise, it is set to zero. The grey-level image is converted to a binary image, as there are only two levels of interest, the foreground ridges and the background valleys.

III. Proposed Method

All This section describes the methods for constructing a series of image enhancement techniques for fingerprint images. The algorithm I have implemented is built on the techniques developed by Hong et al. This algorithm consists of four main stages:

- Normalization,
- Orientation estimation,
- Ridge frequency estimation, and
- Gabor filtering.

In addition to these four stages, I have implemented three additional stages that include:

- Segmentation,
- Binarisation, and
- Thinning.

In this section, I will discuss the methodology for each stage of the enhancement algorithm, including any modifications that have been made to the original techniques.

A. Normalization

The next step in the fingerprint enhancement process is image normalization. Normalisation is used to standardise the intensity values in an image by adjusting the range of grey-level values so that it lies within a desired range of values. Let $I(i; j)$ represent the grey-level value at pixel $(i; j)$, and $N(i; j)$ represent the normalized grey-level value at pixel $(i; j)$. The normalized image is defined as:

$$N(i,j) = \begin{cases} M_0 \pm \sqrt{\frac{V_0 (I(i,j) - M)^2}{v}} \; if \quad I(i,j) > M \,/\, otherwise \end{cases} \qquad (3.2)$$

Where, M and V are the estimated mean and variance of $I(i; j)$, respectively, and M_0 and V_0 are the desired mean and variance values, respectively. Normalisation does not change the ridge structures in a fingerprint; it is performed to standardise the dynamic levels of variation in grey-level values, which facilitates the processing of subsequent image enhancement stages.

B. Orientation Estimation

The orientation field of a fingerprint image defines the local orientation of the ridges contained in the fingerprint (see Figure 3.1.). The orientation estimation is a fundamental step in the enhancement process as the subsequent Gabor filtering stage relies on the local orientation in order to effectively enhance the fingerprint image. The least mean square estimation method employed by Hong et al. is used to compute the orientation image. However, instead of estimating the orientation block-wise, I have chosen to extend their method into a pixel-wise scheme, which produces a finer and more accurate estimation of the orientation field. The steps for calculating the orientation at pixel $(i; j)$ are as follows:

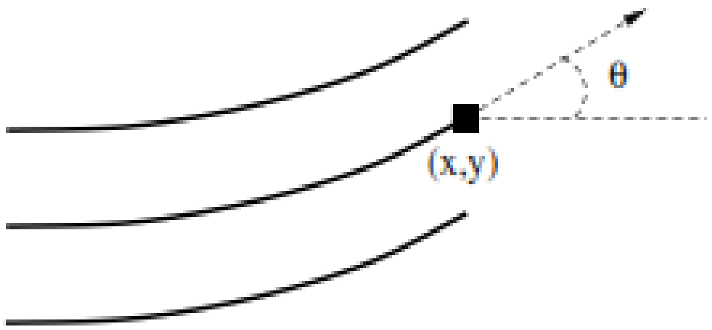


Figure 3.1: The orientation of a ridge pixel in a fingerprint.

1. Firstly, a block of size WxW is centered at pixel $(i; j)$ in the normalized fingerprint image.
2. For each pixel in the block, compute the gradients $\partial_x(i,j)$ and $\partial y(i,j)$ which are the the gradient magnitudes in the x and y directions, respectively. The horizontal Sobel operator is used compute $\partial_x(i,j)$

$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \qquad (3.3)$$

The vertical Sobel operator is used to compute $\partial y(i,j)$

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \qquad (3.4)$$

3. The local orientation at pixel $(i; j)$ can then be estimated using the following equations:

$$V_x(i,j) = \sum_{u=i=\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j=\frac{w}{2}}^{j+\frac{w}{2}} 2\partial_x(u,v)\partial_y(u,v) \qquad (3.5)$$

$$V_x(i,j)=\sum_{u=i=\frac{w}{2}}^{i+\frac{w}{2}}\sum_{v=j=\frac{w}{2}}^{j+\frac{w}{2}}2\partial_x^{\,2}(u,v)\partial_y^{\,2}(u,v) \tag{3.6}$$

$$\theta(i,j)=\frac{1}{2}\tan^{-1}\frac{V_y(i,j)}{V_x(i,j)} \tag{3.7}$$

where, $\mu(i;j)$ is the least square estimate of the local orientation at the block centered at pixel $(i;j)$.

4. Smooth the orientation field in a local neighborhood using a Gaussian filter. The orientation image is firstly converted into a continuous vector field, which is defined as:

$$\Phi_x(i,j)=\cos(2\theta(i,j)) \tag{3.8}$$

$$\Phi_y(i,j)=\sin(2\theta(i,j)) \tag{3.9}$$

where, Φ_x and Φ_y are the x and y components of the vector field, respectively. After the vector field has been computed, Gaussian smoothing is then performed as follows:

$$\Phi_x^{'}(i,j)=\sum_{u=-\frac{w_\phi}{2}}^{\frac{w_\phi}{2}}\sum_{v=-\frac{w_\phi}{2}}^{\frac{w_\phi}{2}}G(u,v)\Phi_x(i-uw,j-vw) \tag{3.10}$$

$$\Phi_y^{'}(i,j)=\sum_{u=-\frac{w_\phi}{2}}^{\frac{w_\phi}{2}}\sum_{v=-\frac{w_\phi}{2}}^{\frac{w_\phi}{2}}G(u,v)\Phi_y(i-uw,j-vw) \tag{3.11}$$

where, G is a Gaussian low-pass filter of size w_Φ X w_Φ.

5. The final smoothed orientation field O at pixel $(i;j)$ is defined as:

$$O(i,j)=\frac{1}{2}\tan^{-1}\frac{\Phi'_y(i,j)}{\Phi'_x(i,j)} \tag{3.12}$$

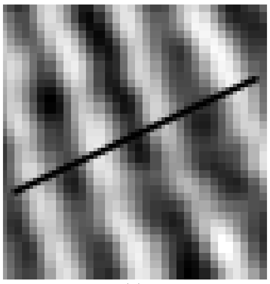
C. RidgeFfrequency Estimation

In addition to the orientation image, another important parameter that is used in the construction of the Gabor filter is the local ridge frequency. The frequency image represents the local frequency of the ridges in a fingerprint. The first step in the frequency estimation stage is to divide the image into blocks of size W X W. The next step is to project the grey-level values of all the pixels located inside each block along a direction orthogonal to the local ridge orientation. This projection forms an almost sinusoidal-shape wave with the local minimum points corresponding to the ridges in the fingerprint. An example of a projected waveform is shown in Figure 3.2.

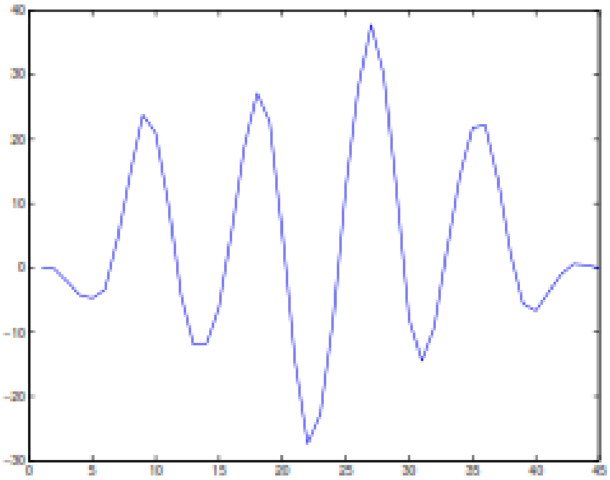
I have modified the original frequency estimation stage used by Hong et al. to include an additional projection smoothing step prior to computing the ridge spacing. This involves smoothing the projected waveform using a Gaussian low-pass filter of size w X w to reduce the effect of noise in the projection. The ridge spacing $S(i;j)$ is then computed by counting the median number of pixels between consecutive minima points in the projected waveform. Hence, the ridge frequency $F(i;j)$ for a block centered at pixel $(i;j)$ is defined as:

$$F(i,j) = \frac{1}{S(i,j)} \tag{3.13}$$

Given that the fingerprint is scanned at a fixed resolution, then ideally the ridge frequency values should lie within a certain range. However, there are cases where a valid frequency value cannot be reliably obtained from the projection. Examples are when no consecutive peaks can be detected from the projection, and also when minutiae points appear in the block. For the blocks where minutiae points appear, the projected waveform does not produce a well-defined sinusoidal-shape wave, which can lead to an inaccurate estimation of the ridge frequency. Thus, the out of range frequency values are interpolated using values from neighboring blocks that have a well-defined frequency.



(a)



(b)

Figure 3.2: The projection of the intensity values of the pixels along a direction orthogonal to the local ridge orientation. (a) A 32 *X* 32 block from a fingerprint image. (b) The projected waveform of the block.

D. Gabor Filtering

Once the ridge orientation and ridge frequency information has been determined, these parameters are used to construct the even-symmetric Gabor filter. A two-dimensional Gabor filter consists of a sinusoidal plane wave of a particular orientation and frequency, modulated by a Gaussian envelope [4]. Gabor filters are employed because they have frequency-selective and orientation-selective proper-ties. These properties allow the filter to be tuned to give maximal response to ridges at a specific orientation and frequency in the fingerprint image. There-fore, a properly tuned Gabor filter can be used to effectively preserve the ridge structures while reducing noise.

The even-symmetric Gabor filter is the real part of the Gabor function, which is given by a cosine wave modulated by a Gaussian (see Figure 2.3). An even-symmetric Gabor filter in the spatial domain is defined as [10]:

$$G(x,y;\theta,f) = \exp\left\{-\frac{1}{2}\left[\frac{x_\theta^{\ 2}}{\sigma_x^{\ 2}} + \frac{y_\theta^{\ 2}}{\sigma_y^{\ 2}}\right]\right\}\cos(2\pi f x_\theta) \tag{3.14}$$

$$x_\theta = x\cos\theta + y\sin\theta \tag{3.15}$$

$$y_\theta = -x\sin\theta + y\cos\theta \tag{3.16}$$

where, μ is the orientation of the Gabor filter, f is the frequency of the cosine wave, ¾$_x$ and ¾$_y$ are the standard deviations of the Gaussian envelope along the x and y axes, respectively, and x_μ and y_μ define the x and y axes of the filter coordinate frame, respectively.

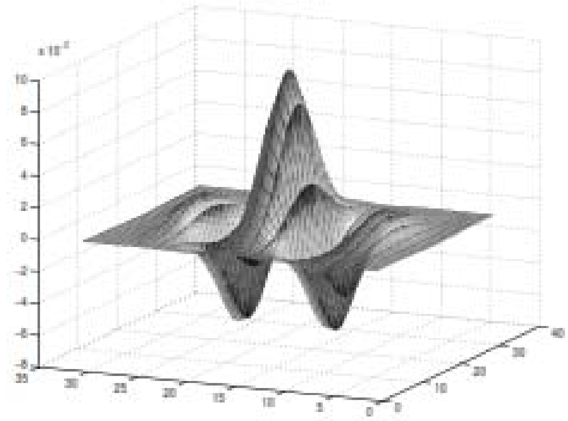


Figure 3.3: An even-symmetric Gabor filter in the spatial domain.

The Gabor filter is applied to the fingerprint image by spatially convolving the image with the filter. The convolution of a pixel (*i; j*) in the image requires the corresponding orientation value *O*(*i; j*) and ridge frequency value *F* (*i; j*) of that pixel. Hence, the application of the Gabor filter *G* to obtain the enhanced image *E* is performed as follows:

$$E(i,j) = \sum_{u=-\frac{w_y}{2}}^{\frac{w_x}{2}} \sum_{v=-\frac{w_y}{2}}^{\frac{w_y}{2}} G(u,v;O(i,j))N(i-u,j-v) \tag{3.17}$$

where, O is the orientation image, F is the ridge frequency image, N is the normalized fingerprint image, and w_x and w_y are the width and height of the Gabor filter mask, respectively.

The filter bandwidth, which specifies the range of frequency the filter responds to, is determined by the standard deviation parameters ¾$_x$ and ¾$_y$. Since the bandwidth of the filter is tuned to match the local ridge frequency, then it can be deduced that the parameter selection of ¾$_x$ and ¾$_y$ should be related with the ridge frequency. However, in the original algorithm by Hong et al., ¾$_x$ and ¾$_y$ were empirically set to fixed values of 4:0 and 4:0, respectively.

A drawback of using fixed values is that it forces the bandwidth to be constant, which does not take into account the variation that may occur in the values of the ridge frequency. For example, if a filter with a constant bandwidth is applied to a fingerprint image that exhibits significant variation in the frequency values, it could lead to non-uniform enhancement or other enhancement artifacts. Thus, rather than using fixed values, I have chosen the values of ¾$_x$ and ¾$_y$ to be a function of the ridge frequency parameter, which are defined as:

$$\sigma_x = k_x F(i,j) \tag{3.18}$$

$$\sigma_y = k_y F(i.j) \tag{3.19}$$

where, F is the ridge frequency image, k_x is a constant variable for ¾$_x$, and k_y is a constant variable for ¾$_y$. This allows a more adaptable approach to be used, as the values of ¾$_x$ and ¾$_y$ can now be specified adaptively according to the local ridge frequency of the fingerprint image.

Furthermore, in the original algorithm, the width and height of the filter mask were both set to fixed values of 11. The filter size controls the spatial extent of the filter, which ideally should be able to accommodate the majority of the useful Gabor waveform information. However, a fixed filter size is not optimal in that it does not allow the accommodation of Gabor waveforms of different sized bandwidths. Hence, to allow the filter size to vary according to the bandwidth of the Gabor waveform, I have set the filter size to be a function of the standard deviation parameters:

$$w_x = 6\sigma_x \tag{3.20}$$

$$w_y = 6\sigma_y \tag{3.21}$$

where, w_x and w_y are the width and height of the Gabor filter mask, respectively, and ¾$_x$ and ¾$_y$ are the standard deviations of the Gaussian envelope along the *x* and *y* axes, respectively. In the above equation, the width and height of the filter mask are both specified as 6¾, due to most of the Gabor wave information being contained within the region [¡3¾; 3¾] away from the *y* axis. Hence, this selection of parameters allows the filter mask to capture the majority of the Gabor waveform information.

E. Segmentation

The first step of the fingerprint enhancement algorithm is image segmentation. Segmentation is the process of separating the foreground regions in the image from the background regions. The foreground regions correspond to the clear fingerprint area containing the ridges and valleys, which is the area of interest. The background corresponds to the regions outside the borders of the fingerprint area, which do not contain any valid fingerprint information. When minutiae extraction algorithms are applied to the background regions of an image, it results in the extraction of noisy and false minutiae. Thus, segmentation is employed to discard these background regions, which facilitates the reliable extraction of minutiae.

In a fingerprint image, the background regions generally exhibit a very low grey-scale variance value, whereas the foreground regions have a very high variance. Hence, a method based on variance thresholding [16] can be used to perform the segmentation. Firstly, the image is divided into blocks and the grey-scale variance is calculated for each block in the image. If the variance is less than the global threshold, then the block is assigned to be a background region; otherwise, it is assigned to be part of the foreground. The grey-level variance for a block of size *W X W* is defined as:

$$V(k0 = \frac{1}{W^2}\sum_{i=0}^{w-1}\sum_{j=0}^{w-1}(I(i,j) - M(k))^2 \tag{3.1}$$

where, $V(k)$ is the variance for block k, $I(i; j)$ is the grey-level value at pixel $(i; j)$, and $M(k)$ is the mean grey-level value for the block k.

F. Binarisation

Most minutiae extraction algorithms operate on binary images where there are only two levels of interest: the black pixels that represent ridges, and the white pixels that represent valleys. Binarisation is the process that converts a grey-level image into a binary image. This improves the contrast between the ridges and valleys in a fingerprint image, and consequently facilitates the extraction of minutiae.One useful property of the Gabor filter is that it has a DC component of zero, which means the resulting filtered image has a mean pixel value of zero. Hence, straightforward binarisation of the image can be performed using a global threshold of zero. The binarisation process involves examining the grey-level value of each pixel in the enhanced image, and, if the value is greater than the global threshold, then the pixel value is set to a binary value one; otherwise, it is set to zero. The outcome is a binary image containing two levels of information, the foreground ridges and the background valley the average of the grey-level values within an image window at each pixel, and if the average is greater than the threshold, then the pixel value is set to a binary value of one; otherwise, it is set to zero. The grey-level image is converted to a binary image, as there are only two levels of interest, the foreground ridges and the background valleys.Overall, it can be seen that most techniques for fingerprint image enhancement are based on filters that are tuned according to the local characteristics of fingerprint images. Both of the examined techniques employ the ridge orientation information for tuning of the filter. However, only the approach by Hong et al. takes into account the ridge frequency information, as Sherlock's approach assumes the ridge frequency to be constant. By using both the orientation and ridge frequency information, it allows for accurate tuning of the Gabor filter parameters, which consequently leads to better enhancement results. Hence, I have chosen to employ the Gabor filtering approach by Hong et al. to perform fingerprint image enhancement.

G. Thinning

The final image enhancement step typically performed prior to minutiae extraction is thinning. Thinning is a morphological operation that successively erodes away the foreground pixels until they are one pixel wide. A standard thinning algorithm [7] is employed, which performs the thinning operation using two sub iterations. This algorithm is accessible in MATLAB via the `thin' operation under the bwmorph function. Each sub iteration begins by examining the neighborhood of each pixel in the binary image, and based on a particular set of pixel-deletion criteria, it checks whether the pixel can be deleted or not. These sub iterations continue until no more pixels can be deleted.The application of the thinning algorithm to a fingerprint image preserves the connectivity of the ridge structures while forming a skeletonised version of the binary image. This skeleton image is then used in the subsequent extraction of minutiae. The process involving the extraction of minutiae from a skeleton image will be discussed in the next chapter.

IV. Conclusion

Overall, I have implemented a set of reliable techniques for fingerprint image enhancement and minutiae extraction. These techniques can then be used to facilitate the further study of the statistics of fingerprints. In addition, these techniques can be also employed in other fingerprinting applications such as fingerprint matching and classification.

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