Ridge Enhancement in Fingerprint Images Using Oriented Diffusion

Robert Hastings
School of Computer Science & Software Engineering
The University of Western Australia, Australia.
email: bobh@csse.uwa.edu.au

Abstract

The extraction of "Level 2" detail — ridge terminations, ridge bifurcations, bridges etc. — from digitised images of fingerprints requires an accurate segmentation of the image into ridges and valleys. Small breaks and irregularities in the ridge pattern occur as a result of imperfections in the print capture process that, if not rectified, give rise to many false level 2 features at later stages of the analysis.

We propose a method for enhancing the ridge pattern by applying a process of oriented diffusion, which is an adaptation of anisotropic diffusion. This acts to smooth the image only in the direction parallel to the ridge flow. The result is an image in which intensity varies smoothly as one traverses along the ridges or valleys, with most of the small irregularities and breaks removed, but with the identity of the individual ridges and valleys preserved. The method offers the advantage of requiring no prior estimate of the ridge frequency.

Results show improved performance by comparison with the method of enhancement using frequency-tuned filters, which sometimes performs well but may produce erroneous results if the filter is tuned to a frequency that does not match the actual ridge frequency.

1 Introduction

1.1 Fingerprint feature extraction

Identification of an individual via fingerprint analysis has traditionally relied on having a fixed number of **point matches** based on the ridge pattern. A point match is a single minutia (level 2 feature), such as a ridge termination or a ridge bifurcation, that is identified in both the input print and in the data print to which it is being matched. Clearly it is desirable to automate the process as much as possible, provided this can be done reliably.

A typical feature extraction algorithm begins by extracting the ridge orientation at each point. A ridge representation is then generated by refining the ridges to eliminate imperfections such as small gaps and jagged edges; this step is sometimes termed "purification". Some kind of binarisation is then done to segment the image into ridges and valleys. In some cases a thinning algorithm is used to create a "skeleton image" of the ridges. The binary ridge map, or sometimes the skeleton image, is then analysed to identify the location and orientation of the minutiae, which then form the basis for comparing one fingerprint with another.

It is the step of refining the ridges that is the subject of this paper.

1.2 Ridge enhancement

A minutia is defined as a point where a ridge terminates or bifurcates [1]. There is more than one way to define the boundary between valleys and ridges; one way is to use an intensity threshold, possibly one that varies from one part of the image to another.

In most fingerprint images, the ridges appear as dark lines on a lighter background. Errors in generating the binary ridge map therefore result from abnormally bright points within a ridge, or abnormally dark points within a valley. These may be due to dust or dirt on the fingerprint itself, noise in the image capture process, cuts, abrasions or wrinkles on the fingertip (which interrupt the flow of the ridges), irregular deposition of ink (in inked prints) and the fine structure of the ridges themselves, eg. the location of sweat pores, or irregularities of the ridge edges. Whatever the source, unless the effect of these artifacts is reduced or eliminated, the final binary ridge map will contain many unwanted features such as small gaps in the ridges, tiny "island ridges" within a valley, or tiny spurs branching off from the ridges. These features give rise to many false minutiae, since a minutia is recognised as a ridge termination or a ridge bifurcation (which is equivalent to a valley termina-

[1] Various subspecies of minutia, eg. spurs, bridges, islands etc. are referred to in the classification literature, but they can all be expressed in terms of combinations of the two main types: ridge terminations and ridge bifurcations.

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tion).

The traditional method of reducing noise in a digital image is to apply some kind of smoothing, using for example a 2-dimensional Gaussian filter. In the case of fingerprint images, however, the typical spacing between the ridges is about 0.5mm [1, pp 63-64] :[5, p 83]), which in a standard 500d.p.i. image equates to approximately 10 pixels. This limits the amount of smoothing that can be carried out using omnidirectional filters. What is required is a method of iteratively smoothing the image in the direction of the ridge orientation but not in the perpendicular direction, thereby preserving the identity of the ridges and valleys.

One popular approach to ridge enhancement [5, P 107] is to use a bank of contextual filters tuned to a specific ridge frequency. The image is smoothed by selecting the appropriate filter at each point, based on the known ridge orientation and on some estimate of the ridge frequency.. For example, O'Gorman and Nickerson [6] employed a bank of oriented filters that were elongated in the direction of the ridge orientation and cosine tapered in the direction at right angles to the ridges. Hong, Wan and Jain [4] employ a bank of oriented Gabor filters. A problem with these kinds of filter however is that, since they are tuned to specific frequencies, they require a preliminary estimate of the ridge frequency. Frequency may vary significantly across the image, and inaccuracies in this point-wise frequency estimate may degrade the performance of the contextual filters, as shown by the results of applying oriented Gabor filtering to a test image (see Figure 1). Moreover, one might expect the frequency estimate to be unreliable near the ridge terminations and bifurcations, which are precisely the regions of most interest.

Our method of ridge enhancement using oriented diffusion seeks to overcome this problem by applying directional smoothing. The method depends on first finding an accurate map of the ridge orientation, but no prior knowledge or estimate of the ridge frequency is needed.

2 Obtaining the ridge orientation

Notation: In this paper the symbol λ_T is used to denote the image distance in pixels that corresponds to a typical ridge pattern wavelength. The typical inter-ridge distance is about 0.5mm (section 1.2); our text images have a resolution of 500d.p.i., so that this distance corresponds in our images to about ten pixels. For this work we use $\lambda_T = 9.84$ pixels, which corresponds to exactly 0.5mm.

There are two inputs to our ridge enhancement process: the orientation field, and an input image that will be enhanced to produce the final ridge map.

To derive the orientation map we use the standard technique of Principal Component Analysis as described by Bazen and Gerez [2]. Additionally, we propose a postprocessing stage to overcome the effect of isolated lines that cross the ridges but are not part of the ridge pattern. Figure 2 shows a fingerprint image containing two such features.

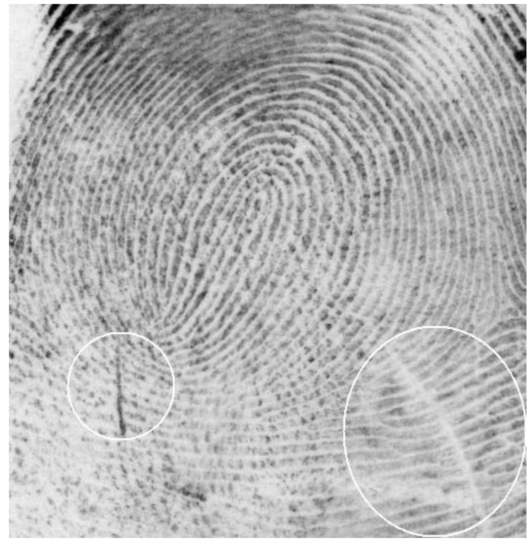


Figure 2. Portion of a fingerprint showing two extraneous linear features (encircled). Obtaining an accurate orientation map requires correction for such features.

These lines may result from:

- Hand-drawn markings or ruled lines — these are normally dark.
- Scars or wrinkles on the fingertip — these show as breaks in the ridges and therefore appear as light in colour.

Such features, because they are highly linear, may distort the orientation field in their vicinity. If this is not corrected, ridge enhancement will produce erroneous results, because the diffusion will take place along the wrong direction.

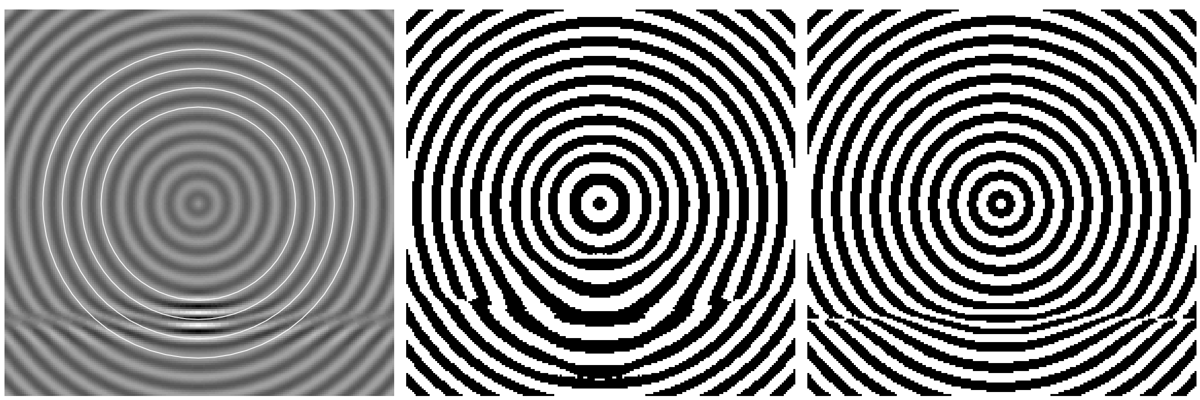
Firstly, to minimise the likelihood of our orientation estimate being confused by highly directional features that are not part of the ridge pattern, we apply a frequency bandpass filter. The reason for using a filter of this nature is that we have some *a priori* knowledge of the ridge frequencies on the fingertips (section 1.2). By setting the frequency cutoff values f_{min} and f_{max} respectively to half and double the average ridge frequency $1/\lambda_T$, we ensure that the estimate of ridge orientation will be based only on features with a realistic periodicity.

Principal Component Analysis is then carried out by sampling a small neighbourhood of each point in the image and determining the direction in which the greatest variability in the image intensity is observed. The measure of

(a) Test image. Actual ridge frequency is 0.1 (i.e. the wavelength is 10 pixels).

(b) Output, filter frequency $= 0.1$. The corrupting feature is well handled. Degradation is noticeable near the centre, but tolerable.

(c) Output, filter frequency $= 0.07$. Significant degradation is apparent near the location of the corrupting feature, and also near the centre where the central intensity maximum has become a minimum.



(d) Output, filter frequency $= 0.15$. Significant degradation is apparent.

(e) Binarised output, filter frequency = 0.07

(f) Binarised output, filter frequency = 0.15

Figure 1. Result of applying oriented Gabor filters to a test image designed to show the behaviour in image regions containing bands with varying curvature, overlain by a corrupting linear feature. The image consists of concentric periodic rings with frequency 0.1, overdrawn by a dark horizontal band 4 pixels in width. In each case the filter spread in both the parallel and perpendicular directions was equal to the tuned wavelength.

Significant degradation occurs for filters tuned to the wrong frequency. Overlaid circles in (c) and (d) indicate the location of intensity peaks in the original image, showing that the intensity maxima appear displaced from the correct positions. This has led to the appearance of false endings and bifurcations in the binarised outputs.

variability is the mean square of the intensity gradient along that direction. The ridges are then expected to be aligned at right angles to this direction of maximum variability.

For any subregion of the image, it can be shown that the direction θ_{max} for which the weighted mean squared gradient of image intensity is a maximum is given by:

$$2\theta_{max} = \text{atan2}(P, D) \tag{1}$$

where:

- $P = 2\overline{g_x g_y}$
- $D = \overline{g_x^2} - \overline{g_y^2}$
- g_x is the image gradient in the x direction,
- g_y is the image gradient in the y direction,
- $\overline{g_x^2}$, $\overline{g_y^2}$ etc. refer to the weighted means of these quantities over the image subregion.

For our work we take the weighted means by applying a 2-dimensional Gaussian filter. The spread σ of the filter defines the size of the subregion and hence the resolution of the orientation estimate; in our case we set σ equal to λ_T.

For each point in the image, equation (1) gives two values of θ_{max} (differing by $180°$) for which the mean squared gradient is a maximum; the two directions at right angles to these therefore give the orientation of the ridges.

Next, in order to reduce and hopefully eliminate the effect of isolated linear features that are not part of the ridge pattern, a postprocessing is performed on the orientation map as follows:

1. Find areas where the anisotropic energy terms D and P vary rapidly as one moves in a direction perpendicular to the orientation.

2. In these regions, replace the values of P and D that were used in equation (1) by new values of P and D derived by using a smoothing filter to interpolate P and D from the surrounding regions.

3. Derive a revised orientation map by applying equation (1), using the new values of P and D.

In carrying out the first of the above steps, it is not sufficient to simply observe the variation of D and P; these quantities are determined by local image intensity as well as the ridge orientation, so that a large rate of change in D or P may simply reflect a rapid variation in image brightness or contrast. To overcome this problem we define the dimensionless quantity U at each image point as:

$$U = \frac{Z}{\overline{|Z|}} \tag{2}$$

where

$$Z = D + iP \tag{3}$$

Here $\overline{|Z|}$ refers to the weighted mean of $|Z|$ obtained by applying a Gaussian filter with spread equal to λ_T. The resultant quantity U is a complex number whose phase is determined by the ridge orientation and whose magnitude is close to 1 except near a flow singularity, where the value falls smoothly to zero [2]. The threshold condition is then expressed as a constraint on the magnitude of the second derivative of U taken in the direction θ perpendicular to the ridges:

$$|U_\theta^{''}| < T \tag{4}$$

for some threshold T. A value for T of $0.5/\lambda_T^2$ is found to eliminate most of the problematic line features; since $U_\theta^{''}$ has units of $1/(pixels)^2$, the division by λ_T^2 makes this threshold condition independent of the image resolution..

3 Ridge enhancement

We wished to perform a ridge enhancement that did not require an *a priori* estimate of the frequency field. We employ a methodology that we term **oriented diffusion**.

The concept underlying diffusion is that a system is allowed to evolve over time, with the state at any point being modified at any given time according to the states of its neighbours. Price et al. [8], for example, take the reaction-diffusion equation as used in chemistry and adapt the concept to processing various kinds of images, making brief mention of its use in enhancing a fingerprint image. Chen and Dong [3] apply anisotropic diffusion to the task of improving their estimate of the orientation field in a fingerprint image. Firstly an initial estimate is generated via the gradient-based method as used in the present work, then the orientation field is smoothed by diffusion in successive stages. The diffusion coefficient is allowed to vary over the image, being smaller in regions of high curvature.

Perona and Malik [7] note that the traditional means of smoothing by convolving with Gaussian filters is analogous to diffusion, with successive smoothing stages corresponding to successive points in time during the diffusion process. They use the term "anisotropic diffusion" to describe their methodology of edge detection, in which they allow the diffusion coefficient to vary in accordance with the current estimate of proximity to a region boundary, being smaller near the boundaries.

In the present work however we do not seek to minimise diffusion at the boundaries of the ridge and valley regions; rather, we wish the amount of smoothing to be the same

[2] Since $|Z|$ is never negative, and is zero only at points located precisely at a singularity, the spatially averaged value $\overline{|Z|}$ is always non-zero even at or near a singularity.

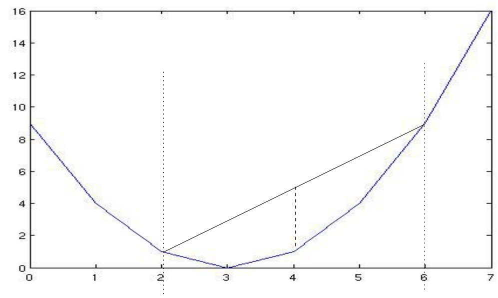


Figure 3. Illustrating that the difference between the mean of a function and the value at the mid-point is related to the second derivative of the function.

right across the ridge, but for the diffusion to take place along one direction only.

To show how this can be achieved, first consider the case of a 1-dimensional signal (Figure 3).

For a smoothly varying function, the mean over an interval differs from the function value at the interval's mid-point by an amount that is determined by the degree of concavity or convexity of the function, i.e. by the second derivative. More formally, if the function in the neighbourhood of the point x_0 can be expressed as the summation of a Taylor series:

$$f(x) = f(x_0) + (x - x_0)f^{'}(x_0) + \frac{1}{2}(x - x_0)^2 f^{''}(x_0) + \dots \tag{5}$$

then a weighted mean of f centred on x_0 is given by:

$$\begin{aligned} \overline{f(x)} &= f(x_0) + \frac{1}{2}\overline{(x - x_0)^2} f^{''}(x_0) + \dots \\ &= f(x_0) + k f^{''}(x_0) + \dots \end{aligned} \tag{6}$$

where $k = \frac{1}{2}\overline{(x - x_0)^2}$ is a constant whose value depends on the size of the chosen interval and on the nature of the weighting function used in taking the means, but not on the behaviour of f itself. (Note that the mean displacement from x_0 is zero, so that the first-order derivative term vanishes, as do all the higher odd-order derivative terms.) If the weighted mean is taken by convolving with a Gaussian filter of spread σ, then k is simply equal to $\sigma^2/2$.

This illustrates that rather than taking a weighted mean using a 1-dimensional smoothing filter, an alternative is to make use of equation (6) by estimating the second derivative, multiplying by an appropriate constant k, and adding this to the value at the reference point.

This becomes useful when we consider functions over a 2-dimensional domain, because the second derivative $f_\theta^{''}(x, y)$ along an axis forming an angle θ with the x-axis is given by:

$$f_\theta^{''}(x, y) = \frac{\partial^2 f}{\partial x^2}\cos^2\theta + \frac{\partial^2 f}{\partial y^2}\sin^2\theta + 2\frac{\partial^2 f}{\partial x \partial y}\cos\theta\sin\theta \tag{7}$$

Accordingly, we perform oriented smoothing in an iterative fashion as follows:

1. The raw image is preprocessed using a bandpass filter similar to that used in determining the ridge orientation, but with a much lower minimum cutoff frequency ($f_{min} = 0.1/\lambda_T$). Exclusion of these very low frequencies means that the intensity across the image is roughly constant when averaged over scales greater than $10\lambda_T$. This normalised image becomes the input for the first iteration.

2. At each iteration:

   - Obtain the three second-order partial derivatives over the image. [3]
   - Set θ to be the ridge orientation, and use equations (6) and (7) to obtain the directionally smoothed value at each point.
   - The output at each stage then becomes the input image for the following stage.

   The same orientation map is used at every stage.

The degree of improvement at each stage may be assessed by taking the sum over the whole image of the changes from one iteration to the next, disregarding the sign of the changes. If we denote this quantity by $\Sigma(\Delta)$, it is found that at first the value of $\Sigma(\Delta)$ falls of in approximately exponential fashion, as might be expected if the process is converging to a well smoothed image. Eventually however the rate of decrease of $\Sigma(\Delta)$ with each iteration slows down markedly, suggesting that little further improvement (even in relative terms) is possible from then on (Figure 4). This point of diminishing returns depends on the quality of the original image, but usually occurs somewhere between 50 and 100 iterations. For this reason 100 iterations was decided upon as an appropriate point at which to terminate the process.

Once the directionally smoothed fingerprint image is obtained, it still remains to perform a binary segmentation into ridge and valley regions. We do this applying a very narrow 2-D Gaussian smoothing filter ($\sigma = 0.3\lambda_T$), and then examining the sign of the second derivative in the direction at right angles to the ridges. This recognises the fact that the second derivative of a a smoothly varying function is positive in the neighbourhood of a local minimum and negative

[3] The first order derivatives are estimated by taking finite differences, eg. $\partial f/\partial x \approx [f(x+1) - f(x-1)]/2$. Similarly, second order derivatives are estimated by taking finite differences of the first order derivatives.

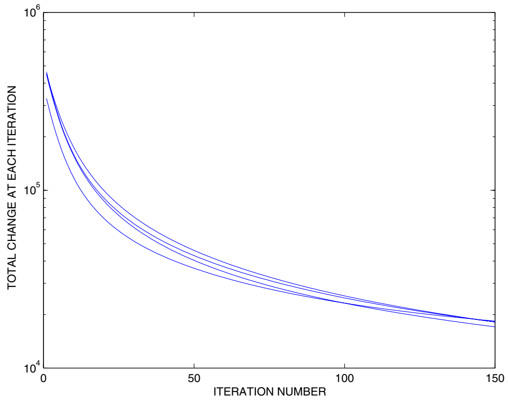


Figure 4. Absolute values of change summed over the entire image (logarithmic scale) at each iteration of oriented diffusion, shown for several typical fingerprint images.

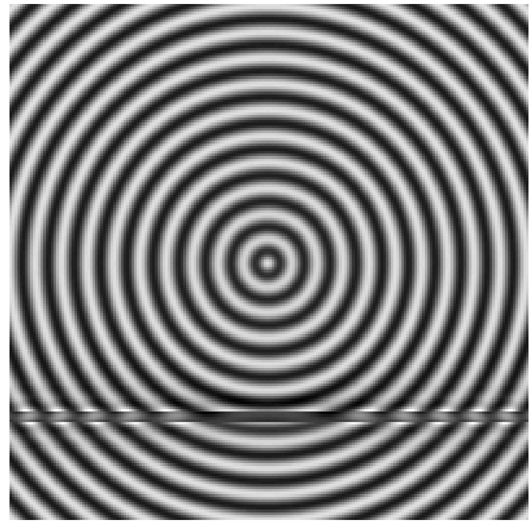


Figure 5. Output from the application of oriented diffusion to the test image. Little degradation is apparent even after 100 iterations.

near a local maximum. This quantity is obtained by again applying equation (7), but replacing θ by $\theta + \pi/2$.

4 Results

The oriented diffusion process was applied to the circular ridges test image shown in Figure 1(a). The quality of the resultant output (Figure 5) is comparable to that from a bank of oriented Gabor filters tuned to the correct frequency, and markedly superior to the outputs obtained from filters whose frequency differs from the correct frequency by a factor of 1.5, which were shown in Figure 1. Ridge frequency variations of this order within a single print, and between prints, are not uncommon. While the diffusion process did not completely remove the corrupting feature, it should be noted that the broad dark band in the test image is an extreme example of the kind of corruption that could be encountered in real images. The important thing to note is that, unlike the contextual filters, the diffusion process did not degrade the regions near the band, which were initially free of corruption.

Figure 6 shows the results of applying the method of oriented diffusion to a typical fingerprint.

For purposes of comparison, the oriented Gabor filter technique was applied to the same image (Figure 7). The orientation field used for selecting the appropriate filter was the same as the orientation field used in applying the oriented diffusion. The actual ridge frequency in this image varied between 0.08 and 0.1; results are shown for contextual filtering at each of these tuning frequencies. Note in particular the degradation in the top left corner of the image, where insufficient smoothing along the ridges has resulted in the appearance of many spurious breaks and joins.

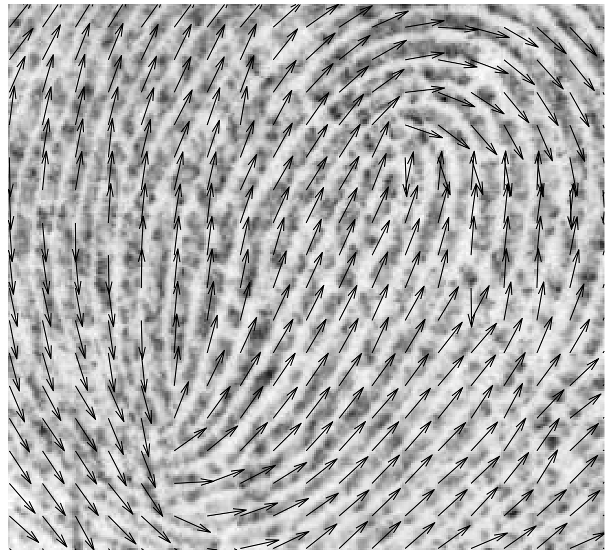
There is a region in the lower left corner of the image (below the lower of the two cores) where neither the oriented diffusion method nor the Gabor filter enhancement gave a clear pattern; this occurred because the image quality at this point was too poor to give a realistic estimate of orientation (Figure 6(b)). Such regions are easily identified by virtue of the fact that the anisotropic energy is small compared to the total energy, avoiding the detection of false minutiae in these regions.

5 Conclusion

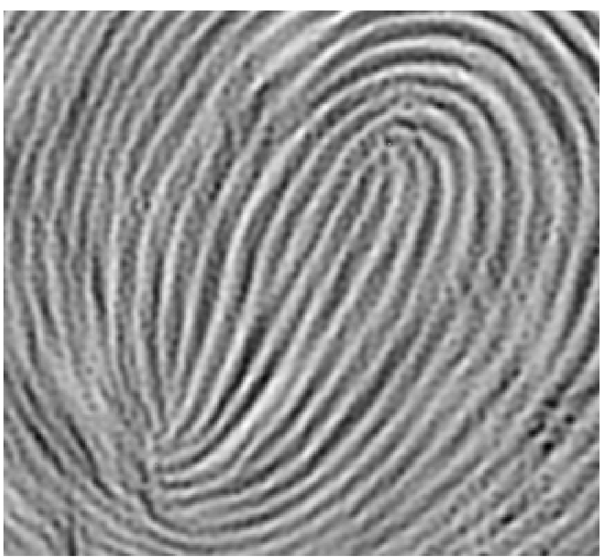
The method of oriented diffusion, when used in conjunction with a reliable ridge orientation map, is an effective way of improving the clarity of the ridge pattern. Performance shows improvement over the method of contextual smoothing filters, which require having at hand a realistic frequency estimate as well as an accurate orientation field.

The availability of such enhanced ridge images should facilitate the task of the human fingerprint examiner, as well as being useful as input to the later stages of automated fingerprint feature extraction, viz. the location and classification of the minutiae.

(a) Portion of the original fingerprint image. Note the corrupting feature consisting of a heavy vertical line at lower left.



(b) Original image with orientation field overlaid.



(c) Directionally smoothed image.

(d) Binarised smoothed image.

Figure 6. Output at various stages of oriented diffusion

(a) Result of smoothing, filter frequency = 0.08.

(b) Result of binarisation of Figure 7(a).

(c) As for figure 7(b), but using a filter frequency of 0.1.

Figure 7. Output from smoothing with a bank of oriented Gabor filters, presented for comparison. Note the poor performance in the upper left region and in the area below and to the right of the lower core.

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