Fingerprint Matching using Gabor Filters

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Abstract: *We present a fingerprint matching scheme that utilizes a ridge feature map to match fingerprint images. The technique described here obviates the need for extracting minutiae points to match fingerprint images. The proposed scheme uses a set of 16 Gabor filters, whose spatial frequencies correspond to the average inter-ridge spacing in fingerprints, is used to capture the ridge strength at equally spaced orientations. A circular tessellation of filtered image is then used to construct the ridge feature map. This ridge feature map contains both global and local details in a fingerprint as a compact fixed length feature vector. The fingerprint matching is based on the Euclidean distance between two corresponding feature vectors. The genuine accept rate of the Gabor filter based matcher is observed to be ~ 10% to 15% higher than that of minutiae-based matcher at low false accept rates. Fingerprint feature extraction and matching takes ~ 7.1 seconds on a Pentium IV, 2.4 GHz processor.*

Keywords: *Biometrics, Gabor filters, fingerprints, matching, verification, core point*

1. INTRODUCTION

Fingerprint-based identification is one of the most important biometric technologies which has drawn a substantial amount of attention recently. Humans have used fingerprints for personal identification for centuries and the validity of fingerprint identification has been well established. In fact, fingerprint technology is so common in personal identification that it has almost become the synonym of biometrics. Fingerprints are believed to be unique across individuals and across fingers of same individual. Even identical twins having similar DNA, are believed to have different fingerprints. These observations have led to the increased use of automatic fingerprint-based identification in both civilian and law-enforcement applications.

A fingerprint is the pattern of ridges and furrows on the surface of a fingertip. Ridges and valleys are often run in parallel and sometimes they bifurcate and sometimes they terminate. When fingerprint image is analyzed at global level, the fingerprint pattern exhibits one or more regions where ridge lines assume distinctive shapes. These shapes are characterized by high curvature, terminations, bifurcations, cross-over etc. These regions are called singular regions or singularities. These singularities may be classified into three topologies; loop, delta and whorl. At local level, there are other important features known as minutiae can be found in the fingerprint patterns. Minutiae means small details and this refers to the various ways that the ridges can be discontinuous. A ridge can suddenly come to an end which is called termination or it can divide into two ridges which is called bifurcations (Figure 1).

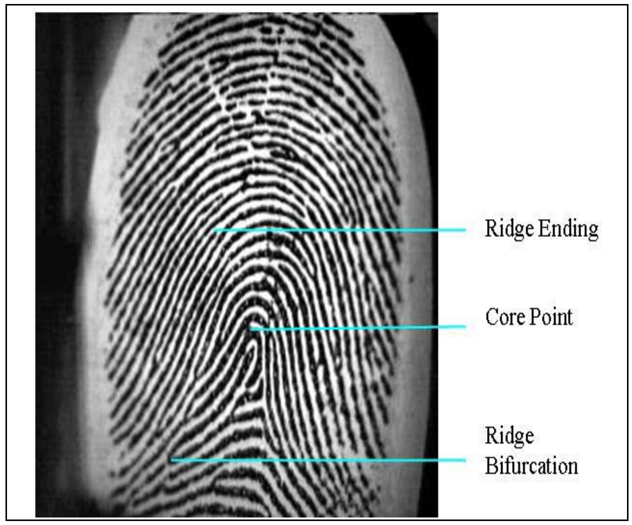

Figure 1: Ridge ending, core point and ridge bifurcation is shown.

2. FINGERPRINT MATCHING

Fingerprint matching techniques can be broadly classified as minutiae based and correlation based [1]. Minutiae-based technique first locates the minutiae points in a given fingerprint image and matches their relative placements in a stored template fingerprint. A good quality fingerprint contains between 60 and 80 minutiae, but different fingerprints have different number of minutiae. The performance of minutiae-based techniques rely on the accurate detection of minutiae points and the use of sophisticated matching techniques to compare two minutiae fields which undergo non-rigid transformations. Correlation based techniques compare the global pattern of ridges and valleys to see if the ridges in the two fingerprints align. The global approach to fingerprint representation is typically used for indexing [2] and does not offer reliable fingerprint discrimination.

The ridge structure in a fingerprint can be viewed as an oriented texture patterns having a dominant spatial frequency and orientation in a local neighborhood. The frequency is due to inter ridge-spacing present in a fingerprint and the orientation is due to the flow pattern exhibited by ridges. Most textured images contain a narrow range of spatial frequencies. For a typical fingerprint images scanned at 500 dpi, there is a little variation in the spatial frequencies among different fingerprints. This implies that there is an optimal scale (spatial frequency) for analyzing the fingerprint texture. By capturing the frequency and orientation of ridges in local regions in the fingerprint, a distinct representation of the fingerprint is possible [3].

The proposed scheme first detects the core point in a fingerprint image using two different techniques. Core point is defined as the north most point of inner-most ridge line. In practices, the core point corresponds to center of north most loop type singularity. Some fingerprints do not contain loop or whorl singularities, therefore it is difficult to define core. In that kind of images, core is normally associated with the maximum ridge line curvature. Detecting a core point is not a trivial task; therefore two different techniques have been used to detect optimal core point location. A circular region around the core point is located and tessellated into 128 sectors. The pixel intensities in each sector are normalized to a constant mean and variance. The circular region is filtered using a bank of sixteen Gabor filters to produce a set of sixteen filtered images. Gabor filter-banks are a well known technique to capture useful information in specific band pass channels. Two such techniques have been discussed in [3] and [4]. The average absolute deviation with in a sector quantifies the underlying ridge structure and is used as a feature. The feature vector (2048 values in length) is the collection of all the features, computed from all the 128 sectors, in every filtered image. The feature vector captures the local information and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The matching stage computes the Euclidean distance between the two corresponding feature vectors.

It is desirable to obtain representations for fingerprints which are translation and rotation invariant. In the proposed scheme, translation is taken care of by a reference point which is core point during the feature extraction stage and the image rotation is handled by a cyclic rotation of the feature values in the feature vector. The features are cyclically rotated to generate feature vectors corresponding to different orientations to perform the matching.


Figure 2: Optimal core point location

3. CORE POINT DETECTION

Two different methods are used to detect core point in a fingerprint image (Figure 2). The core point location is more accurately detected by using multiple techniques.

3.1 Core point detection using Poincare index

1) Estimate the orientation field *O* using the least square orientation estimation algorithm [5]. Orientation field *O* is defined as an *M x N* image, where *O(i,j)* represents the local ridge orientation at pixel *(i,j)*. An image is divided into a set of w x w non-overlapping blocks and a single orientation is defined for each block.

2) Initialize *A*, a label image used to indicate the core point.

3) For each pixel *(i,j)* in *O*, compute Poincare index [2] and assign the corresponding pixels in *A* the value of one if Poincare index is between 0.45 and 0.51.The Poincare index at pixel *(i,j)* enclosed by a digital curve, which consists of sequence of pixels that are on or within a distance of one pixel apart from the corresponding curve, is computed as follows:

$$\text{Poincare}(i,j) = 1/(2\pi) \sum_{k=0}^{Np-1} \Delta(k) \qquad (1)$$

$$\Delta(k) = \begin{cases} \delta(k) & \text{if } |\delta(k)| < \pi/2 \\ \pi + \delta(k) & \text{if } \delta(k) \le -\pi/2 \\ \pi - \delta(k) & \text{otherwise} \end{cases} \qquad (2)$$

$$\delta(k) = \theta(x_{(k+1) \bmod Np}, y_{(k+1) \bmod Np}) - \theta(x_k, y_k) \qquad (3)$$

For our method, *Np* is selected as 8.

4) The center of block with the value of one is considered to be the center of fingerprint. If more than one block has value of one, then calculate the average of coordinates of these blocks.

3.2 Core point detection using slope

1) Estimate the orientation field *O* using the least square orientation estimation algorithm [5].

2) Smooth the orientation field in local neighborhood. Let the smoothed orientation field be represented as *O'*.

3) Initialize *A*, a label image used to indicate the core point.

4) In *O'(i , j)* , start from first row *(0, 0),* find the block whose angle is between 0 and π /2 and then trace down vertically until a block with a slope not with in

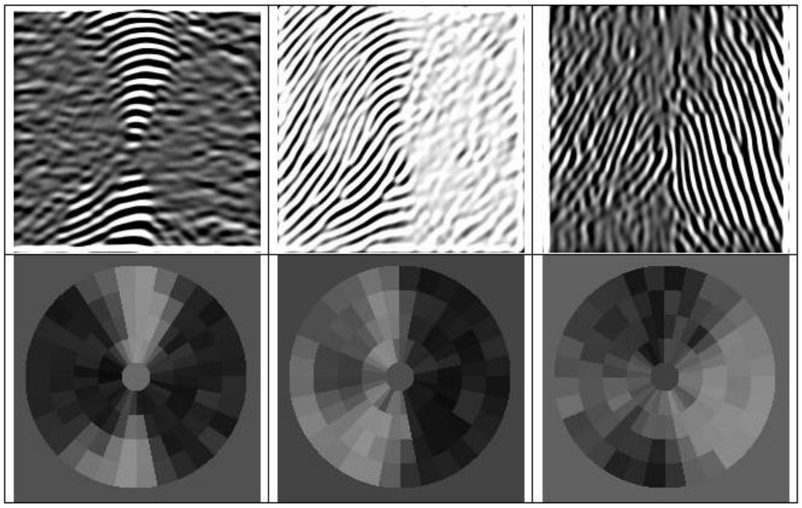

Figure 3: Filtered images and their corresponding feature vectors for orientations 0^{o}, 22.5^{o}, and 45^{o} are shown.

that range (0 and π /2) is encountered. That block is then marked [6] in *A*. This procedure is performed on all the rows of orientation field *O'(i,j)*.

5) The center of block with the highest number of marks is considered to be the center of fingerprint.

3.3 Optimal Core Point

Now we have two core point locations obtained from above two techniques. Optimal core point is then calculated by taking average of x-coordinate values and taking the maximum of two y-coordinate values as maximum y-coordinate is more precise location of core point.

4. TESSELLATION

The spatial tessellation of fingerprint image which consists of the region of interest is defined by a collection of sectors. We use four concentric bands around the core point. Each band is 20 pixels wide and segmented into thirty two sectors. Thus we have a total of 32 x 4 = 128 sectors and the region of interest is a circle of radius 100 pixels, centered at the core point.

5. NORMALIZATION

Normalization is performed to remove the effects of sensor noise and gray level background due to finger pressure differences. For all the pixels in sector *Si*, where i $\in$ (0,1,2….127), the normalized image is defined as:

$$Ni(x,y) = \begin{cases} M_0 + \sqrt{\dfrac{V_o \times (I(x,y) - M_i)^2}{V_i}} & \text{if } I(x,y) > Mi \\ M_0 - \sqrt{\dfrac{V_o \times (I(x,y) - M_i)^2}{V_i}} & \text{otherwise} \end{cases} \quad (4)$$

Mi and Vi are estimated mean and variance of grey levels in sector Si respectively. M_o and V_o are the desired mean and variance values, respectively. For our experiments, both M_o and V_o are set to a value of 50.

6. FILTERING

Gabor filters optimally capture both local orientation and frequency information from a fingerprint image. By tuning a Gabor filter to specific frequency and direction, the local frequency and orientation information can be obtained [2][3] as shown in Figure 3. Thus, they are suited for extracting texture information from images [4]. Daugman has successfully used these filters to extract discriminatory features from human iris [7].

An even symmetric Gabor filter has the following general form in the spatial domain:

$$G(x,y\,;\,f,\theta) = \exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_{x'}^2} + \frac{y'^2}{\delta_{y'}^2}\right]\right\}\cos(2\pi f x') \quad (5)$$

$$x' = x \sin\theta + y \cos\theta \quad (6)$$

$$y' = x \cos\theta - y \sin\theta \quad (7)$$

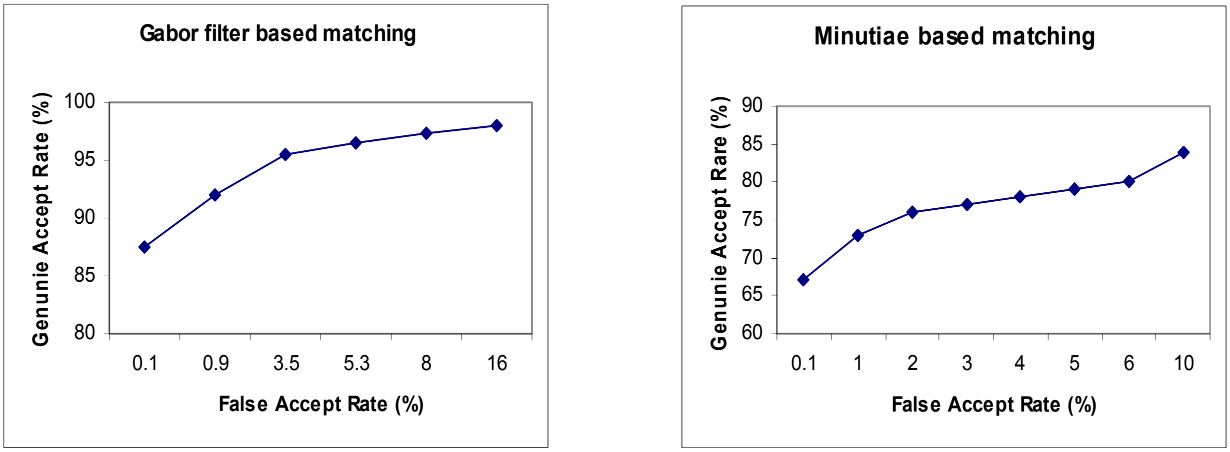

Figure 4: The ROC curve comparing the performance of the Gabor filter based approach with the minutiae based approach

where f is the frequency of the sinusoidal plane wave along the direction θ from the x-axis, and δ_x and δ_y are the space constants of the Gaussian envelope along x and y axes, respectively.

The filtering is performed in the spatial domain with a mask size of 17x17. The frequency f is the average ridge frequency (1/K), where K is the average inter ridge distance. The average inter ridge distance is approximately 10 pixels in a 500 dpi fingerprint image. Hence, f = 1/10. Sixteen different orientations are examined. These correspond to θ values of 0, 11.25, 22.5, 33.75, 45, 56.25, 67.5, 78.75, 90, 101.25, 112.5, 123.75, 135, 146.25, 157.5 and 168.75 degrees. The values for $\delta_{x'}$ and $\delta_{y'}$ were empirically determined and each is set to 4 (about half the average inter ridge distance).

7. FEATURE VECTOR

Let $F_{i\theta}(x, y)$ be the θ-direction filtered image for sector Si. Now, $\forall$ i $\in$ (0,1,2….127) and θ $\in$ (0, 11.25, 22.5, 33.75, 45, 56.25, 67.5, 78.75, 90, 101.25, 112.5, 123.75, 135, 146.25, 157.5, 168.75 degrees) the feature value, $V_{i\theta}$, is the average absolute deviation from the mean defined as:

$$V_{i\theta} = \frac{1}{n_i}\left[\sum_{n_i}\left|F_{i\theta}(x, y) - P_{i\theta}\right|\right] \tag{8}$$

where n_i is the number of pixels in S_i and $P_{i\theta}$ is the mean of pixel values of $F_{i\theta}(x, y)$ in sector S_i. The average absolute deviation of each sector in each of the sixteen filtered images defines the components of our 2048-dimensional feature vector [4]. The average absolute deviation from the mean of each sector in each of the sixteen filtered images defines the components of our feature vector.

The rotation invariance is achieved by cyclically rotating the features in a feature vector itself. A single step cyclic rotation of the features corresponds to a feature vector which would be obtained if the image was rotated by 11.25 degrees.

Fingerprint matching is based on finding the Euclidean distance between the corresponding feature vectors. This minimum score corresponds to the best alignment of the two fingerprints being matched. If the Euclidean distance between two feature vectors is less than a threshold, then the decision that “the two images come from the same finger” is made, otherwise a decision that “the two images come from different fingers” is made. Since the template generation for storage in the database is an off-line process, the verification time still depends on the time taken to generate a single template.

8. EXPERIMENTAL RESULTS

The database of fingerprint images contains 180 images. There are eight different impressions per finger. The performance of biometric system can be shown as a Receiver Operating Characteristic (ROC) curve that plots the Genuine Accept Rate (GAR) against the False Accept Rate (FAR) at different thresholds on the matching score. We compare this performance with a minutiae-based approach [4][8]. As can be seen in Figure 4, our approach outperforms the minutiae based approach over wider range of FAR values. For example, at 1% FAR, the Gabor filter based fingerprint matcher gives a GAR of 91% while the minutiae based matcher gives a GAR of 73%.

The Gabor filter based fingerprint technique takes ~ 7.1 seconds on Pentium – IV, 2.4 GHz processor, for feature extraction and matching. About 95% of the total time i.e. ~

6.7 seconds, is taken by the convolution of the input image with 16 Gabor filters. The convolution operation can be made significantly faster by dedicated DSP processors. If the core point is correctly located, the features are translation invariant and the rotation handled in the matching stage is very fast. As a result, the matching process is extremely fast.

9. SUMMARY AND FUTURE WORK

We have presented a fingerprint matching scheme that utilizes both the frequency and orientation information available in a fingerprint. Sixteen Gabor filters are used to extract features from the template and input images. The primary advantage of our approach is improved translation and rotation invariance. The following areas of improvement are also being studied:

(1) New matching methods for comparing the ridge feature maps of two images

(2) Constructing the ridge feature maps using adaptive methods for optimal selection of Gabor filters

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