# A Novel approach for Fingerprint Matching using Gabor Filters

Dhamal Rajani Balaso
*SCOEM, Limb, Satara*

**Abstract—With identity fraud in our society reaching unprecedented proportions and with an increasing emphasis on the emerging automatic personal identification applications, biometrics-based verification, especially fingerprint-based identification, is receiving a lot of attention. There are two major shortcomings of the traditional approaches to fingerprint representation. For a considerable fraction of population, the representations based on explicit detection of complete ridge structures in the fingerprint are difficult to extract automatically. The widely used minutiae-based representation does not utilize a significant component of the rich discriminatory information available in the fingerprints. Local ridge structures cannot be completely characterized by minutiae. Further, minutiae-based matching has difficulty in quickly matching two fingerprint images containing different number of unregistered minutiae points. The proposed filter-based algorithm uses a bank of Gabor filters to capture both local and global details in a fingerprint as a compact fixed length FingerCode. The fingerprint matching is based on the Euclidean distance between the two corresponding FingerCodes and hence is extremely fast.**

**Keywords—Biometrics, FingerCode, fingerprints, flow pattern, Gabor filters, matching, texture, verification.**

## I. INTRODUCTION

With the advent of electronic banking, e-commerce, and smartcards and an increased emphasis on the privacy and security of information stored in various databases, *automatic* personal identification has become a very important topic. Accurate automatic personal identification is now needed in a wide range of civilian applications involving the use of passports, cellular telephones, automatic teller machines, and driver licenses. Traditional knowledge-based [password or personal identification number (PIN)] and token-based (passport, driver license, and ID card) Identifications are prone to fraud because PIN's may be forgotten or guessed by an imposter and the tokens may be lost or stolen. As an example, MasterCard credit card fraud alone now amounts to more than 450 million U.S.dollars annually.

*Biometrics*, which refers to identifying an individual based on his or her physiological or behavioral characteristics, has the capability to reliably distinguish between an authorized person and an imposter. Among all the biometrics (e.g., face, fingerprints, hand geometry, iris, retina, signature, voice print, facial thermogram etc), fingerprint-based identification is one of the most mature and proven technique. A fingerprint is the pattern of ridges and valleys on the surface of the finger. The uniqueness of a fingerprint can be determined by the overall pattern of ridges and valleys as well as the local ridge anomalies [a ridge bifurcation or a ridge ending,] called minutiae points. As fingerprint sensors are becoming smaller and cheaper, automatic identification based on fingerprints is becoming an attractive alternative/complement to the traditional methods of identification. The critical factor in the widespread use of fingerprints is in satisfying the performance (e.g., matching speed and accuracy) requirements of the emerging civilian identification applications. Some of these applications (e.g., fingerprint- based smartcards) will also benefit from a compact representation of a fingerprint.

## II. FINGERPRINT MATCHING

Fingerprint matching techniques can be broadly classified as minutiae based and correlation based. Minutiae based technique [1][2] 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 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. By capturing the frequency and orientation of ridges in local regions in the fingerprint, a distinct representation of the fingerprint is possible.

The proposed scheme of feature extraction tessellates the region of interest of the given fingerprint image with respect to a reference point. A feature vector is composed of an ordered enumeration of the features extracted from the (local) information contained in each subimage (sector) specified by the tessellation. Thus, the feature elements capture the local information and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The local discriminatory information in each sector needs to be decomposed into separate components. Gabor filterbanks are a well-known technique to capture useful information in specific bandpass channels as well as to decompose this information into biorthogonal components in terms of spatial frequencies. A feature vector, which we call FingerCode, is the collection of all the features (for every sector) in each filtered image. These features capture both the global pattern of ridges and valleys and the local characteristics. Matching is based on the Euclidean distance between the FingerCodes.

## III. FILTER-BASED FEATURE EXTRACTION

It is desirable to obtain representations for fingerprints which are scale, translation, and rotation invariant. Scale invariance is not a significant problem since most fingerprint images could be scaled as per the dpi specification of the sensors. The rotation and translation invariance could be accomplished by establishing a reference frame based on the intrinsic fingerprint characteristics which are rotation and translation invariant. The present implementation of feature extraction assumes that the fingerprints are vertically orientation. In reality, the fingerprints in our database are not exactly vertically oriented; the fingerprints may be oriented up to away from the assumed vertical orientation. This image rotation can be partially handled by a cyclic rotation of the feature values in the FingerCode in the matching stage; in future implementations. The four main steps in our feature extraction algorithm are

1) Determine a reference point and region of interest for the fingerprint image;
2) Tessellate the region of interest around the reference point;
3) Filter the region of interest in eight different directions using a bank of Gabor filters .
4) Compute the average absolute deviation from the mean (AAD) [4] of gray values in individual sectors in filtered images to define the feature vector or the FingerCode. In the current implementation, our system performs matching as shown in Figure1.

### *A. REFERENCE POINT DETECTION*

Fingerprints have many conspicuous landmark structures and a combination of them could be used for establishing a reference point. We define the reference point of a fingerprint as the point of maximum curvature of the concave ridges of fingerprint image.

An improved scheme for core point positioning algorithm [6] that we have used is as follows.

1) Given an input image, enhance [7] the fingerprint in order to obtain a better image quality.
2) After this operation, the image is segmented and background is separated from fingerprint image. This can be performed using a simple block-wise variance approach, since background is usually characterized by a small variance. Image is first binary closed (Matlab command imclose), then eroded (Matlab command imerode), in order to avoid holes in fingerprint image and also undesired effect at the boundary (between fingerprint and background). The image segmentation is repeated several times, up to a desired condition is satisfied. This is done in order to avoid undesired boundary effects between fingerprint and background. The condition which has to be satisfied is chosen in the following way: the enhanced image is divided into non-overlapping blocks of given sizes (usually 32 x 32 or 64x64). The whole enhanced image is filtered with a complex filter [8]. Let Cf_max be the maximum value of the filtered image in the current region of interest (previously calculated according to some initial parameters). For each non-overlapping block we calculate the relative maximum Cf_rel.
3) Then we perform a fast pixel-wise orientation field computation [9].
4) The orientation field is used to obtain a logical matrix where pixel (I,J) is set to 1 if the angle of the orientation is <= PI/2 (PI 3.1415926535897...).
5) After this computation find the border of this logical matrix, in the region of interest of fingerprint image.

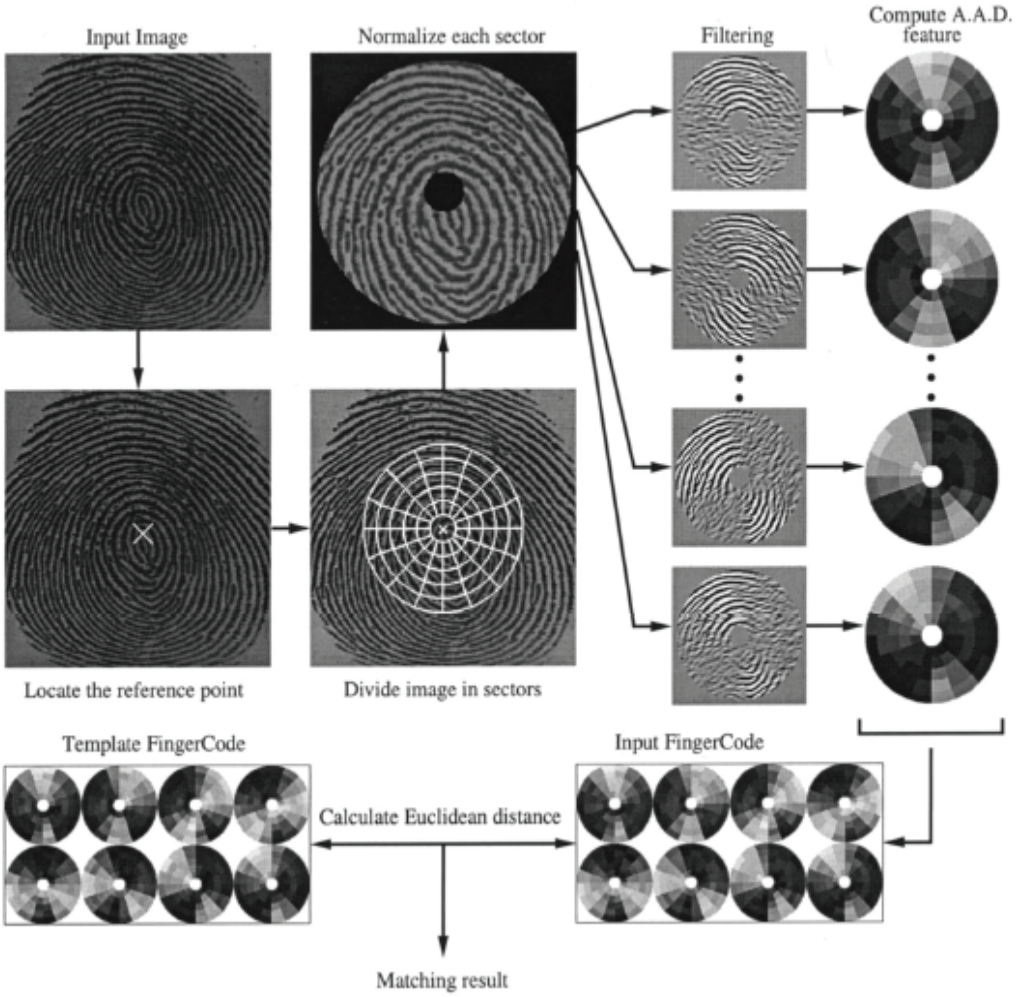


Figure 1: An authentication system using filterbank approach

6) After this computation I calculate the complex filtering output [8] of the enhanced fingerprint image. It is not necessary to re-calculate it, I use the complex filtered image calculated in step 2.

Now we can find the maximum value of complex filtering output where the pixels of the logical image are set to 1.

7) I repeat steps 4-5-6 for a wide set of angles (…, PI/2-3*alfa, PI/2-2*alfa, PI/2-1*alfa, PI/2, PI/2+1*alfa, PI/2+2*alfa, PI/2 +3*alfa, where alfa is an arbitrary angle). Each time I determine a point (Note: each of them will be a candidate for fingerprint matching).

8) Subdivide all the points found in step 7 into subsets of points which are quite near each other. I will have say N subsets. For each subsets I will have a certain number of candidates and I consider only subset with a number of candidates >= 3. For each of this subset I consider the subset with the greatest x-averaged coordinate. In this subset I consider the core point the candidate with the greatest x-coordinate. This is a good approximation in standard fingerprint image.

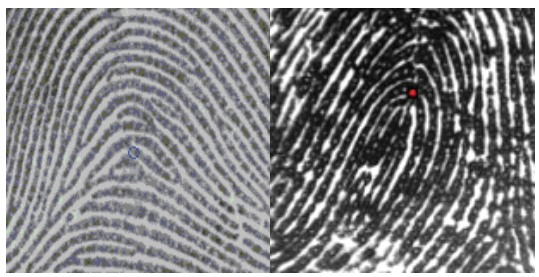

Figure 2. Results of optimal ref point algorithm

*B. TESSELLATION*

The spatial tessellation of fingerprint image which consists of the region of interest is defined by a collection of sectors. We consider Newdb14 database containing 14 TIFF Fingerprint images of size 256 x 256 with resolution 500dpi. We use four concentric bands around the core point. Each band is 20 pixels wide and segmented into sixteen sectors. Thus we have a total of 16 x 4 = 64 sectors and the region of interest is a circle of radius 100 pixels, centered at the core point.

Fingerprints have local parallel ridges and valleys, and well defined local frequency and orientation. Properly tuned Gabor filters [4], [5], can remove noise, preserve the ridge and valley structures, and provide information contained in a particular orientation in the image. A minutia point can be viewed as an anomaly in locally parallel ridges and it is this information that we are attempting to capture using the Gabor filters. Before filtering the fingerprint image, we normalize the region of interest in each sector separately to a constant mean and variance. Normalization is performed to remove the effects of sensor noise and gray level deformation due to finger pressure differences. Let $I(x,y)$denote the gray value at pixel (x,y), and $Mi, Vi$ the estimated mean and variance of sector $Si$, respectively, and $Ni(x,y)$ the normalized gray-level value at pixel (x,y). For all the pixels in sector $Si$, the normalized image is defined as follows

$$N_i(x, y) = \begin{cases} M_0 + \sqrt{\{V_0 * (I(x, y) - M_i)^2/V_i\}} & \text{if } I(x, y) > Mi \\ M_0 - \sqrt{\{V_0 * (I(x, y) - M_i)^2/V_i\}} & \text{otherwise} \end{cases} \quad (1)$$

where $Mo$ and $Vo$ are the desired mean and variance values, respectively.

Normalization is a pixel-wise operation which does not change the clarity of the ridge and valley structures. If normalization is performed on the entire image, then it cannot compensate for the intensity variations in different parts of the image due to the elastic nature of the finger. Separate normalization of each individual sector alleviates this problem.

### C. FILTERING

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

$$G(x, y: f, \theta) = \exp\{-(1/2) * [(x'^2/\delta^2_{x'}) + (y'^2/\delta^2_{y'})]\} * \cos(2\Pi f x') \quad (2)$$

$$x' = x \sin\theta + y \cos\theta \quad (3)$$

$$y' = x \cos\theta - y \sin\theta \quad (4)$$

Where f is the frequency of the sinusoidal plane wave along the direction from the x-axis, and $\delta_x$ and $\delta_y$ are the space constants of the Gaussian envelope along and axes, respectively. We keep value of f=average inter ridge distance i.e. 20 pixel and $\delta_{x\ and}$ $\delta_y$ as half of average distance 0.5.We perform the filtering in the spatial domain with a mask size of 33×33. However, to speed up the filtering process, we perform convolution in frequency domain. We have used eight different values for (0, 22.5, 45, 67.5, 90, 112.5, 135, and 157.5 degrees) with respect to the x-axis for Gabor filter. The normalized region of interest in a fingerprint image is convolved with each of these eight filters to produce a set of eight filtered images. A fingerprint convolved with a $0^0$-oriented filter accentuates those ridges which are parallel to the x-axis and smoothes the ridges in the other directions. Filters tuned to other directions work in a similar way. These eight directional-sensitive filters capture most of the global ridge directionality information as well as the local ridge characteristics present fingerprint.

### D. FEATURE VECTOR

Let $F_{i\theta}$ be the θ-direction filtered image for sector *Si*. Now, and, the feature value $V_{i\theta}$ is the average absolute deviation from the mean $P_{i\theta}$ defined as

$$V_{i\theta} = \frac{1}{n_i}\left[\sum_{n_i}\left|F_{i\theta}(x,y) - P_{i\theta}\right|\right] \quad (5)$$

Where is $n_i$ the number of pixels in *Si* , and $P_{i\theta}$ is the mean of pixel values of $F_{i\theta}$ in sector *Si* . The average absolute deviation of each sector in each of the eight 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 22.5 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.

## IV. EXPERIMENTAL RESULTS

We have tested this algorithm on various databases like SmallDB, NewDB, FingDB, which are taken from Internet.. SmallDB contains 4 different fingerprints of type whorl , right Loop and double loop each fingerprint has size 256×256 and resolution 500 dpi. NewDB is a small database containing the 14 images of size 256×256 and resolution 500 dpi. The FingDB contains PC TIF files corresponding to 21 persons 8 items per person. The images are 256×256 pixels with resolution 500 dpi. when same fingerprint is given as input, or for input fingerprint you consider different rotated images of 10, 90,180,270, degree of each fingerprint ie 1_1.TIF, 2_1.TIF etc which is already in database Then results for FAR, GAR, FRR for threshold are as follows.

| Database | FAR(%) | FRR (%) | GAR(%) |
|---|---|---|---|
| SmallDB | 0 | 6.4 | 93.6 |
| NewDB | 0 | 8.9 | 90.1 |
| FingDB | 0 | 3.7 | 96.3 |

The average matching time is 25 seconds. The memory requirement is 512 bytes per fingerprint. Since this is template matching approach, matching process is very fast. When any fingerprint from this database is given as input fingerprint for matching, It calculates Euclidean distance between input FingerCode and template FingerCode. If

Euclidean distance between input FingerCode and template FingerCode is less than threshold then match occurs otherwise mismatch occurs. Here we consider ideal databases of fingerprint which contains exactly vertically oriented, high quality fingerprints of different person. In future we are working to handle rotated image and poor quality image. Here we need our system become rotation invariant for large amount of rotation. For poor quality image we can enhance image using different image enhancement algorithm.

## IV.CONCLUSION

We have presented a fingerprint matching scheme that utilizes both the frequency and orientation information available in a fingerprint. Eight Gabor filters are used to extract features from the template and input images. The primary advantage of our approach is computationally attractive matching capability and compact length of FingerCode.

The following areas of improvement are needed

1) Handling Distortion
2) Handling Large scale rotation

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