Fingerprint Recognition Using Zernike Moments

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Abstract: *In this paper, we present a fingerprint matching approach based on localizing the matching regions in fingerprint images. The determination of the location of such Region Of Interest (ROI) using only the information related to core points based on a novel feature vectors extracted for each fingerprint image by Zernike Moment Invariant (ZMI) as the shape descriptor. The Zernike Moments is selected as feature extractor due to its robustness to image noise, geometrical invariants property and orthogonal property. These features are used to identify corresponding ROI between two fingerprint impressions by computing the Euclidean distance between feature vectors. The fingerprint matching invariance under translations, rotations and scaling using Zemike Moment Invariants and the experimental results obtained from a FVC2002 DB1 database confirm the Zernike moment is able to match the fingerprint images with high accuracy.*

Keywords: *Fingerprint matching, Region Of Interest, ZMI, feature extractor.*

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1. Introduction

In recent years, the fingerprints are most widely used for identification in many social conditions such as access control, crime investigation, and personal trust. Fingerprint recognition is one of the most mature and proven technique because of their immutability and individuality [7]. Immutability refers to the permanent and unchanged character of the pattern on each finger from before birth until decomposition after death. Individuality refers to the uniqueness of ridge details across individuals even our own two hands are never quite alike.

A large number of fingerprint recognition algorithms have been proposed in literature to date. These matching algorithms may be based on image correlation, texture descriptor and filter banks or minutiae points [7]. Among these, minutiae based algorithms are the most widely used. Most minutiae based algorithms rely on explicit or implicit alignment of the minutiae for matching the two prints. The matching score is determined by counting the corresponding minutiae pairs between both fingerprints two minutiae correspond if a minutia from the test set is located within a bounding box or tolerant zone around a minutia from the template set.

The process of alignment is a combinatorial problem and most matching algorithms have a time complexity. The filterbank based matching algorithm [2] uses a bank of Gabor filters to capture both local and global information in a fingerprint as a compact fixed-length.

Fingerprints images are direction-oriented patterns formed by ridge and valleys. The singular points are the most important global characteristics of a fingerprint. The fingerprints have been classified according to the number of singular points (core, delta) and the location of them [4, 11]. There have been several approaches for the detection of singular points in literature. By far, the most popular method is the one proposed by [5] and is based on the computation of the Poincaré index. The Poincaré index for any given point in a vector field is computed by summing the orientation difference between successive elements along a closed path around that point. Some approaches are based on neural network [3], local energy of directional field [9]. To locate a unique reference point consistently for all types of fingerprints, we define the reference point as the point with maximum curvature on the convex ridge, which is usually located in the central area as shown in Figure 1.

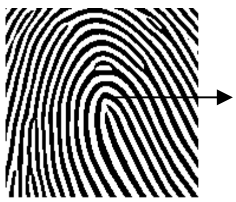

Figure1. The reference point on the convex ridge.

Moments and moments-based image invariants have been used in image recognition extensively [6, 10]. Hu [1] first introduced his seven moment-based image invariants that have the invariance property against affine transformations including rotation, scaling and translation. However, to compute the higher order of Hu's moment invariants is quite complex, and to reconstruct the image from Hu's invariants is also very difficult. To solve these problems, Teague [8] introduced the concept of Zernike moments to recover the image from moment invariants based on the theory of orthogonal polynomials. The reason for used Zernike moments in fingerprint recognition, the image has the invariance property against image rotation, scaling and translation, which is very desirable for robust fingerprint matching. While the magnitudes of the orthogonal Zernike moments are used as rotation-invariant features.

Zernike moments have been shown to be superior to the others in terms of their insensitivity to image noise, information content, and ability to provide faithful image representation [10]. Zemike moments, have been previously used for other biometrics, such as face and gait recognition, signature authentication, watermarking, moving recognition, and showed an encouraging performance.

In this paper, we define the reference point of a fingerprint as the point of maximum curvature in the fingerprint image. Fingerprint recognition is generally composed of five stages. In the first the fingerprint image is enhanced by means of local histogram equalization. Furthermore, and in the second stage detect the reference point (core point) in the fingerprint image, and crop from the fingerprint image a smaller region centered in the reference point, called ROI. The ROI is defined in wxw square shape and it contains sufficient information to represent the fingerprint.. The third stage involves feature extraction by using Zernike Moments Invariant (ZMI) as feature descriptor, so, each feature vector extracted form each ROI used to represent the fingerprint. Euclidean distance is applies to compute the similarity measure of the fingerprint for feature matching in the fourth stage. The final stage requires decision making whether a claimant should be accepted or rejected.

2. Preprocessing

Because there is noise in original fingerprint images, and fingerprint images may be in bad quality, we cannot identify the singular point area efficiently. In order to reduce the influence of noise, we preprocess the input fingerprint images.

2.1. Image Normalization

The objective is to decrease the dynamic range of the gray between ridges and valleys of the image, we normalize the image to constant mean and variance. Normalization is done to remove the effects of sensor noise and finger pressure difference. *I(i,j)* denotes the gray value at pixel *(i,j)*. *M* and *VAR* are the estimated mean and variance of the input fingerprint image.

$$N(i,j)=\begin{cases} M_0+\sqrt{\dfrac{VAR_0 x I(i,j)-M)^2}{VAR}}, if I(i,j) > M \\ M_0-\sqrt{\dfrac{VAR_0 x(I(i,j)-M)^2}{VAR}}, otherwise \end{cases} \quad (1)$$

where M_0 and VAR_0 are the desired mean and variance values.

2.2. Smooth and Histogram Equalization

After normalization, we use Gaussian smoothing to reduce the influence of noises, and we use histogram equalization to make the input fingerprint image look clear.

3. Reference Point Location

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 in the fingerprint image. A summary of reference point location algorithm is presented below [2].

1. Estimate the orientation field *O* using a window size of *w*x*w*.
2. Smooth the orientation field in a local neighborhood. Let the smoothed orientation field be represented as *O'*. In order to perform smoothing (low-pass filtering), the orientation image needs to be converted into a continuous vector field, which is defined as.

$$\Phi_x(i,j)=cos(2O(i,j)) \quad (2)$$

$$\Phi_y(i,j)=\sin(2O(i,j)) \quad (3)$$

where Φ_x *and* Φ_y, are the x and y components of the vector field, respectively. With the resulting vector field, the low-pass filtering can then be performed as.

$$\Phi'_x(i,j)=\sum_{u=-w_\Phi/2}^{w_\Phi/2}\sum_{v=-w_\Phi/2}^{w_\Phi/2}W(u,v).\Phi_x(i-uw,j-vw) \quad (4)$$

$$\Phi'_y(i,j)=\sum_{u=-w_\Phi/2}^{w_\Phi/2}\sum_{v=-w_\Phi/2}^{w_\Phi/2}W(u,v)$$
$$\Phi_y(i-uw,j-vw) \quad (5)$$

where W is a two-dimensional low-pass filter with unit integral and $w_\Phi\,x\,w_\Phi$ specifies the size of the filter. Note that the smoothing operation is performed at the block level. For our experiments, we used a 7x7 mean filter. The smoothed orientation field at is computed as.

$$O'(i,j)=\frac{1}{2}\tan^{-1}\left(\frac{\Phi'_y(i,j)}{\Phi'_x(i,j)}\right) \quad (6)$$

3. Compute ε, an image containing only the sine component of *O'*.

$$\varepsilon(i,j) = sin(O'(i,j)). \tag{7}$$

4. Initialize A, a label image used to indicate the reference point.
5. For each pixel (i,j) in , integrate pixel intensities (sine component of the orientation field). it's designed to capture the maximum curvature in concave ridges. Although this to detects the reference point.
6. Find the maximum value and assign its coordinate to the reference point.

4. Zernike Moments Invariant

Zernike moments a set of complex polynomials $\{V_{nm}(x,y)\}$ which form a complete orthogonal set over the unit disk of $x^2+y^2 \leq 1$, in polar coordinates [8] the form of the polynomials is:

$$V_{nm}(x,y) = V_{nm}(r,\theta) = R_{nm}(r)\exp(jm\theta) \tag{8}$$

where n is positive integer or zero; m is integers subject to constraints n-|m| is even, and $|m| \leq n$; $r = \sqrt{x^2+y^2}$ is the length of the vector from the origin to the pixel (x, y); $\theta = \arctan(y/x)$ is the angle between the vector r and x axis in counterclockwise direction; R_{nm} (r) is Radial polynomial defined as:

$$R_{nm}(r) = \sum_{s=0}^{(n-|m|)/2} \frac{(-1)^s(n-s)!}{s!\left[\frac{n+|m|}{2}-s\right]!\left[\frac{n-|m|}{2}-s\right]!} r^{n-2s} \tag{9}$$

The two-dimensional Zernike moment of order n with repetition m for function $f(x,y)$ is defined as:

$$Z_{nm} = \frac{n+1}{\pi}\iint_{unitdisk} f(x,y)V^*_{nm}(x,y)dxdy \tag{10}$$

where $V^*_{nm}(x,y) = V_{n,-m}(x,y)$.

To compute the Zernike moment of a digital image, we just need to change the integrals with summations:

$$A_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f(x,y)V^*_{nm}(x,y), \tag{11}$$

where $x^2+y^2 \leq 1$.

The defined features of Zernike moments themselves are only invariant to rotation. To achieve scale and translation invariance, the image needs to be normalized first by using the regular Zernike moments.

The translation invariance is achieved by translating the original image $f(x,y)$ to $f(x+\bar{x}, y+\bar{y})$, where $\bar{x} = m_{10}/m_{00}$ and $\bar{y} = m_{01}/m_{00}$.

In other words, the original image's center is moved to the centroid before the Zernike moment's calculation. Scale invariance is achieved by enlarging or reducing each shape so that the image's 0th regular moment m'_{00} equals to a predetermined value β. For a binary image, m_{00} equals to the total number of shape pixels in the image, for a scaled image f(α x, α y) , its regular moments $m'_{pq} = \alpha^{p+q+2} m_{pq}$, m_{pq} is the regular moments of f(x, y).

Since the objective is to make $m'_{00} = \beta$, we can let $\alpha = \sqrt{\beta/m_{00}}$. by substituting $\alpha = \sqrt{\beta/m_{00}}$ into m'_{00}, we can obtain $m'_{00} = \alpha^2 m_{00} = \beta$.

The fundamental feature of the Zernike moments is their rotational invariance. If f(x, y) is rotated by an angle α, then we can obtain that the Zernike moment Z_{nm} of the rotated image is given by

$$Z'_{nm} = Z_{nm}e(-jm\alpha) \tag{12}$$

Thus, the magnitudes of the Zernike moments can be used as rotationally invariant image features.

A fingerprint recognition system is a one-to-one matching process. It matches a person's claimed identity to enrolled pattern. There are two phases in our system: enrollment and verification. Both phases comprise from preprocessing for fingerprint image and detect and crop the ROI, and extract the feature vectors invariant by ZMI features extraction. However, verification phase consists of an additional stage, for calculating the similarity matching of the fingerprint. At the enrollment stage, a set of the template images represented by ZMI features is labeled and stored into a database. At the verification stage, an input image is converted into a set of ZMI features, and then is matched with the claimant's ROI fingerprint image stored in the database to gain the similarity measure. Euclidean distance metric is applied to calculate the similarity between the two feature vectors. Finally, the distance score is then compared with a threshold value to determine whether the user should be accepted.

5. Experimental Results

Experimental studies are carried out on the Database of FVC2002. We take six impressions of 100 different fingers, yielding 600 fingerprint images in the database. Among the six images from each user, three are selected for training while other three are used for testing. We have chosen the ZMI of order 10 for feature extraction, the 36 feature vector invariant to represent each ROI area. The ROI is then used for feature extraction. The extracted ROI of the fingerprint is processed by ZM feature vector extractors to obtain the most discriminating features from the fingerprint for recognition task.

To investigate the performance of ROI, the recognition rate is displayed in Table 1. Experimental result shows that ROI is able to achieve correct recognition rate for ROI a 92.89% is achieved using the Euclidean distance. The system performance can be evaluated by using Equal Error Rate (EER) where FAR=FRR.

Table 1. Testing result of recognition rate.

Type	Correct Recognition Rate
FAR(%)	7.108
FRR(%)	7.151
TSR(%)	92.892
EER(%)	7.130

Figure 2 shows a threshold value is obtained based on Equal Error Rate criteria where FAR=FRR. Threshold value of 0.4132 is achieved when the FAR and FRR are set to 7.108% and 7.151% respectively.

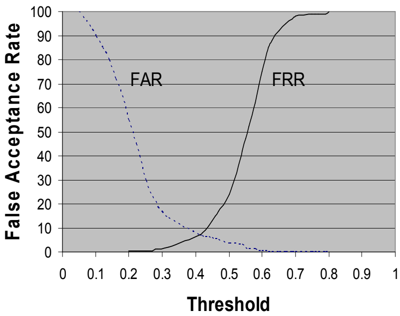

Figure 2. Plotted FAR-FRR graph to obtain threshold.

The overall matching performance can be measured by a Receiver Operating Characteristic (ROC) curve, which plots FRR against FAR at different operating points (distance threshold) Figure 3 illustrates the ROC curve.

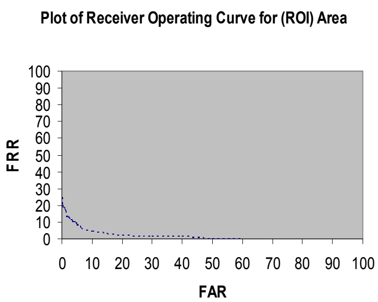

Figure 3. ROC based on testing database

Based on the ROC plotted above in Figure 5 shows the ZMI perform well as feature descriptors on fingerprint images, this vindication of the orthogonality advantage.

Orthogonality property of ZM is able to elicit the unique fingerprint attributes into each order moment with minimum information redundancy.

6. Conclusions

The idea of implementing Zernike moment as fingerprint feature extractors is that they posses a useful rotation invariance property. The new feature vectors are rotation and translation invariant and capture more global information on fingerprint ridges and furrows pattern. In this paper, fingerprint image recognition has been developed by applying a novel ZMI descriptor very valuable in applications of image understandings. Using our feature vector robust to transformation and noise, and the reference point feature is computed efficiently, this conclusion is expected to extend to other moments family.

References

[1] Hu M. K., "Visual Pattern Recognition by Moment Invariants," *IRE Transaction Information Theory*, vol. IT-8, no. 2, pp. 179-187, 1962.

[2] Jain A. k., Prabhaker S., Hong L., and Pankanti S., "Filterbank-Based Fingerprint Matching," *IEEE Transactions on Image Processing*, vol. 9, no. 5, pp. 846-859, 2000.

[3] Kamijo M., "Classifying Fingerprint Images Using Neural Network: Deriving the Classification State", *in Proceedings of the International Conference on Neural Network*, vol. 3, pp. 1932-1937, 1993.

[4] Karu K. and Jain A., "Fingerprint Classification," *Pattern Recognition*, vol. 29, no. 3, pp. 389-404, 1996.

[5] Kawagoe M. and Tojo A., "Fingerprint Pattern Classification," *Pattern Recognition*, vol. 17, no. 3, pp. 295-303, 1984.

[6] Khotanzad A. and Hong Y., "Invariant Image Recognition By Zernike Moments," *IEEE Transactions on Pattern Analysis Machine Intelligent*, vol. 12, no. 5, pp. 489–497, 1990.

[7] Maltoni D., Maio D., Jain A.K., and Prabhakar S., "Handbook of Fingerprint Recognition," Springer-Verlag, New York, 2003.

[8] Mukundan R. and Rmakrishnan K. R., "Moments Functions in Image Analysis Theory and Applications," World Scientific Publishing, Singapore, 1998.

[9] Perona P., "Orientation Diffusions," IEEE *Transactions on Image Processing*, vol. 7, pp. 457-467, 1998.

[10] The C. H. and Chin R. T., "On Image Analysis by the Methods of Moments," *IEEE Transactions on*

Pattern Analysis Machine Intelligent, vol. 10, no. 4, pp. 496–513, 1988.

[11] Wang S. and Wang Y., "Fingerprint Enhancement in the Singular Point Area", *IEEE Singnal processing*, vol. 11, no. 1, pp. 16-19, 2004.

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