

# Fingerprint Matching by Extracting GLCM Features

Benazir . K.K

Department of Computer Science,  
School of Tech.& Applied Sciences,  
MahatmaGandhiUniversity,  
Govtof Kerala, India.

Vijayakumar

Director,  
School of Computer Science,  
MahatmaGandhiUniversity,  
Govt. of Kerala ,India.

## ABSTRACT

Fingerprint matching is an important and challenging problem in fingerprint recognition. Even though so many different methods are there, it has been learned from studies that a better feature extraction technique may lead to very good results. In this paper, we have improved the efficiency of fingerprint matching by combining GLCM based feature extraction with Euclidean based matching. Co-occurrence matrices can be used to extract features from the fingerprint image because they are composed of regular texture patterns. First, the fingerprint image is preprocessed and a unique reference point is determined to secure a Region-of-Interest (ROI). Four co-occurrence matrices are computed from the ROI with a predefined set of parameters. A feature vector consisting of 16 features are used to match the input image with different types of images stored in the database.

The fingerprint matching is based on the Euclidean distance between the two corresponding fingerprints and hence is extremely fast.

The validity of newly derived algorithms is tested on fingerprint images of **Db1\_a&Db1\_bof FVC2002** database. A very good result of 97% of matching is achieved. The method significantly reduces the memory cost and processing time associated with verification, primarily because of the efficient use of GLCM feature extraction.

The experimental results and the ROC curves demonstrate the effectiveness of the proposed method, concerning the feature extraction of ROI, especially in low quality images.

## General Terms

Pattern Recognition.

## Keywords

Fingerprint matching, GLCM, Median filtering, Euclidean distance.

## 1. INTRODUCTION

Compared with other biometrics features, fingerprint-based biometrics is the most proven technique and has the largest market shares. The fingerprint's strength is its acceptance, convenience and reliability. It takes little time and effort for somebody using a fingerprint identification device to have his or her fingerprint scanned. Studies have also found that using fingerprints as an identification means, is the least intrusive of all biometric techniques. In addition, fingerprint identification devices usually require very little space on a desktop or in a machine. Although fingerprint recognition has been studied for many years

and much progress has been made, the performance of even state-of-the-art matchers is still much lower than the expectations of people and theory estimation [1]. Therefore, much effort is still needed to improve both the performance and the speed of fingerprint recognition systems. The matching algorithm plays a key role in a fingerprint recognition system. In this paper, a novel fingerprint matching algorithm is proposed.

*Identification* is the traditional domain of criminal fingerprint matching. A fingerprint of unknown ownership is matched against a database of known fingerprints to associate a crime with an identity. In identification, the input is only a query fingerprint; the system tries to answer the question: Are there any fingerprints in the database that resemble the query fingerprint? The output is a short list of fingerprints [2], [3]. Identification is also termed, *one-to-many matching*.

There is an informal third type of matching that is termed *one-to-few matching*. This is for the practical application where a fingerprint system is used by "a few" users, such as by family members to enter their house.

Here, we are dealing with the *verification* problem. Although fingerprints possess much discriminatory information, and significant progress in automating the verification process has been made, reliable automatic fingerprint verification is still a challenging problem.

Fingerprint matching is one of the most reliable methods of personal verification. A critical step in such systems is to automatically and reliably extract minutiae from the input fingerprint images. Most of the works today in fingerprint are based on minutia based feature extraction. But, fingerprint images are rarely of perfect quality. They may be degraded and corrupted due to variations in skin and impression conditions. So, researchers are facing tremendous challenges related with the accuracy and efficiency by merely adopting minutia based approach.

The idea behind the present paper is to use the co-occurrence matrix and its extracted features in fingerprint matching. To the best of our knowledge, no one has attempted to implement this combination before. The idea is simple and straight forward. For each fingerprint image, a feature vector is formed by converting the generated gray-level co-occurrence matrix (GLCM) to a vector and then it is used for matching.

This paper is organized as follows: Section 2 describes Gray-Level Co-occurrence Matrix (GLCM). Section 3 describes the proposed method. Section 4 gives experimental results and Section 5 draws a conclusion.

## 2. GRAY-LEVEL CO-OCCURRENCE MATRIX (GLCM)

Distribution of pixel gray levels can be described by second-order statistics like the probability of two pixels having particular gray levels at particular spatial relationships. This information can be summarized in two dimensional gray level co-occurrence matrices, which can be computed for various distances and orientations. In order to use information contained in the GLCM, Haralick defined some statistical measures to extract textual characteristics. In this paper 4 features, that can successfully characterise the statistical behavior (experimentally determined), are used.

Some of these features are contrast, correlation, energy, homogeneity, etc. These are

$$1. \text{Contrast} \quad f_1 = \sum_{i,j} |i-j|^2 p(i,j)$$

$$2. \text{Correlation} \quad f_2 = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j}$$

$$3. \text{Energy} \quad f_3 = \sum_{i,j} p(i,j)^2$$

$$4. \text{Homogeneity} \quad f_4 = \sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

Contrast measures the local variation in the gray level of glcm. Correlation measures the joint probability of occurrence of pixel pairs of glcm. Energy gives the sum of squared pixel values and Homogeneity refers to the closeness of distribution of elements to the glcm diagonal. Homogeneous textures contain ideal repetitive structures.

Haralick et al. [4] introduced the Gray-level co-occurrence matrix (GLCM). It is a statistical approach that can describe second-order statistics of a textured image. GLCM is basically a two-dimensional histogram in which the (i, j)th element is the frequency that event i co-occurs with event j. A co-occurrence matrix is specified by the relative frequencies  $P(i, j, d, \theta)$  in which two pixels, separated by distance d, occur in a direction specified by angle  $\theta$ , one with gray level i and the other with gray level j.

A co-occurrence matrix is therefore a function of distance r, angle  $\theta$  as well as grayscales i and j [4].

$$P(i, j, d, \theta) = \#\{((k, l), (m, n)) \in (L_r \times L_c) \times (L_r \times L_c) \mid k-m=0, |l-n|=d, I(k, l) = i, I(m, n) = j\} \quad (2.1)$$

$$P(i, j, d, 45) = \#\{((k, l), (m, n)) \in (L_r \times L_c) \times (L_r \times L_c) \mid (k-m=d, |l-n|=-d) \text{ or } (k-m=-d, |l-n|=d), I(k, l) = i, I(m, n) = j\} \quad (2.2)$$

$$P(i, j, d, 90) = \#\{((k, l), (m, n)) \in (L_r \times L_c) \times (L_r \times L_c) \mid k-m=d, |l-n|=0, I(k, l) = i, I(m, n) = j\} \quad (2.3)$$

$$P(i, j, d, 135) = \#\{((k, l), (m, n)) \in (L_r \times L_c) \times (L_r \times L_c) \mid k-m=d, |l-n|=d \text{ or } (k-m=-d, |l-n|=-d), I(k, l) = i, I(m, n) = j\} \quad (2.4)$$

where # denotes the number of elements in the set. For computing of the co-occurrence matrix we can take an example. Figure 1. shows a 4x4 image with 4 gray levels.

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

Figure 1. Gray level image, [5]

The co-occurrence matrices for the distance  $d=1$  and angles  $0^\circ, 45^\circ, 90^\circ$ , and  $135^\circ$  are showed in Figure 2.

$$P_0^0 = \begin{bmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix} \quad P_{45}^0 = \begin{bmatrix} 4 & 1 & 0 & 0 \\ 1 & 2 & 2 & 0 \\ 0 & 2 & 4 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$P_{90}^0 = \begin{bmatrix} 6 & 0 & 2 & 0 \\ 0 & 4 & 2 & 0 \\ 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix} \quad P_{135}^0 = \begin{bmatrix} 2 & 1 & 3 & 0 \\ 1 & 2 & 1 & 0 \\ 3 & 1 & 0 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix}$$

Figure 2. The co-occurrence matrices computed for images in Figure 1. using equations (2.1-2.4),  $d=1$ .

## 3. PROPOSED METHOD

The main steps of proposed method are: (i) pre processing the input image. (ii) reference point determination (iii) region-of-interest extraction (iv) GLCM feature extraction from region-of-interest (v) matching.

### 3.1 Preprocessing

The aim of the preprocessing is to improve the image data that suppresses the undesired distortions or enhances some image features, which are important for further processing. Since preprocessing is very useful to suppress information that is not relevant to the specific image processing or analysis task. The preprocessing steps include the following:

- a) Normalization
- b) Median Filtering

#### 3.1.1 Normalization

The first step in the fingerprint enhancement process is image normalization. Normalization is done so that the gray level values lies within a given set of values. The fingerprint image is normalized to have a predefined mean and variance. Normalization involves pixel-wise operations and does not change the ridge and valley structures. This is required, as the image usually has distorted levels of gray values among the ridges and

the valleys. Normalization is used to standardize the intensity values in an image by adjusting the range of gray-level values so that it lies within a desired range of values. Let  $I(i, j)$  denote the gray-level value at pixel  $(i, j)$ ,  $M_0$  and  $V_0$  denote the estimated mean and variance respectively, and  $N(i, j)$  denote the normalized gray-level value at pixel  $(i, j)$ . The normalized image is defined as follows:

$$N(i, j) = \begin{cases} M_0 + \sqrt{\frac{V_0(I(i, j) - M^2)}{V}} & \text{if } I(i, j) > M \\ M_0 - \sqrt{\frac{V_0(I(i, j) - M^2)}{V}} & \text{otherwise,} \end{cases} \quad (3.1.1)$$

Where

$$M(I) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} I(i, j) \quad (3.1.2)$$

and,

$$V(I) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (I(i, j) - M(i, j))^2 \quad (3.1.3)$$

Normalization does not change the ridge structures in a fingerprint; it is performed to standardize the dynamic levels of variation in gray-level values. In this paper, we have used  $M_0=50$  and  $V_0=50$ .



Figure 3. Normalized image

### 3.1.2 Median Filtering

De-noising algorithms might be better if they involve not only the noise, but also the image spatial characteristics [6].

Median Filter is a non-linear smoothing method that may be used when the aim is to achieve noise reduction with a minimum amount of blurring of edges. Thus, it provides a more selective result as compared to the linear methods of filtering. This means that the grey level of each pixel is replaced by the median of the grey levels in a neighborhood of that pixel, instead of by averaging. Median Filter method is particularly effective when the noise pattern consists of strong and spike like components and the characteristic to be preserved is edge sharpness. In order to perform median filtering in a neighborhood of a pixel, the values of the pixel and its neighbors are sorted first, the median is determined, and the value to the pixel is assigned. With median filtering, the value of an output pixel is determined by the median of the neighborhood pixels. The median is much less sensitive than the mean to extreme values (called outliers).

In our experiment, the median filter was applied and got the median filtered fingerprint image as a good quality image for further enhancement. The median filtered

image is shown in the figure 4.(b)



Figure 4 a) Original Fingerprint Image b) Median Filtered Image

### 3.2 Reference Point determination

Reference point detection is the most challenging task. It is an important process for fingerprint image alignment. In fingerprint, rich set of textural features are centered on the reference point area. Accurate determination of reference point is very crucial. The Core Point, located at the approximate center of the finger impression, is used as a reference point for reading and classifying the fingerprint. The most commonly used reference point is the core point. A core point is defined as the point at which maximum direction change is detected in the orientation field of a fingerprint image [7] or the point at which the directional field becomes discontinuous [8].

An approach described in [9] is used in this paper to detect the reference point. Here the importance is given to detect a reference point at which a maximum direction change can be identified in the concave ridges as illustrated in Figure 5.

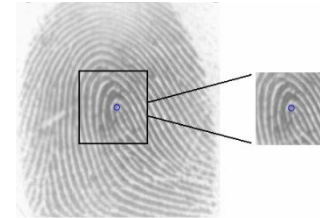


Figure 5. Reference point detected at the concave ridge in an input image (Left) and the extracted ROI (Right)..

### 3.3 Cropping(ROI)

In a fingerprint recognition system, only the scanned image of fingerprint region should be taken into account. Since only a part of the acquired image is interested for further inspection, it is necessary to define a region of interest (ROI). 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. Also, in fingerprint, an area around the reference point has rich textural features which have enough information to produce better results (figure 6).

Using core point as center, we have cropped the image to 100x100 pixels to calculate GLCM feature extraction.



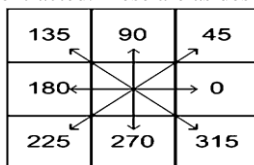
**Figure 6. Cropped image**

Hence, it is necessary that the ROI (Region of Interest) to be segmented from the background by cropping the image, by taking only the most essential texture features. As, co-occurrence matrix calculation is a memory intensive process, using a predefined area (ROI) instead of entire fingerprint image, gives considerable memory reduction.

### 3.4 Feature Extraction

A fingerprint consists of a series of ridges that flow parallel to the locally dominant direction and occasionally make local singularities like a core or delta point. Because of this strong directional information fingerprints possess, the GLCM is thought to be a good candidate for fingerprint feature extraction. In the first stage of feature extraction, the ROI is selected from an input fingerprint image and a square area of 100x 100 pixels around the reference point is utilized for computing GLCM features. The point of maximum curvature of the ridges that are upwardly convex is used as the reference point.

The fingerprint image in its raw form contains the necessary data for successful identification hidden amongst a lot of irrelevant information. Thus image enhancing processes will remove noise and other clutter before the next step of localizing and identifying distinct features, so called feature extraction. A single GLCM might not be enough to describe the textural features of an input fingerprint. For example, a single horizontal spatial relationship might not be sensitive to texture with a vertical orientation. For this reason, multiple GLCMs are computed for values of  $\theta$  at  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$ , and  $135^\circ$ . The relative distance is taken as one pixel. Figure 7 shows the direction and position of other pixels with respect to pixel of interest, which results in four co-occurrence matrices. Based on each computed GLCM, four features that can successfully characterize the statistical behavior of a co-occurrence matrix are extracted. These are as described as below [10]:



**Figure. 7 Eight directions of adjacency**

Feature extraction is carried out as follows: First, for each ROI 4 co-occurrence matrix is computed with predefined set of parameters. Each computed co-occurrence matrix is used to get 4 set of GLCM features to form a total of 16 features. Four features used in four angle (0 degree, 45 degree, 90 degree, 135 degree) directions producing 16 features.

### 3.5 Matching using Euclidean distance

Reliably matching fingerprint images is an extremely difficult problem, mainly due to the large variability in different impressions of the same finger (i.e., large intra-class variations). Fingerprints from the same finger may sometimes look quite different whereas fingerprints from different fingers may appear quite similar. The purpose of fingerprint matching is to determine whether two fingerprints, template and input, are from the same finger.

The matching module determines whether two different fingerprint representations (extracted features from test finger and feature template) are impressions of the same finger [11,12]. Fingerprint matching algorithms usually adopt a two-stage strategy; firstly the correspondence between the feature sets are recognized and secondly the actual matching is performed [12,11]. The matching algorithm defines a metric (the match score) of the similarity between the two fingerprint feature sets and a comparison with a system defined decision threshold results in a match or a non-match. The value of the decision threshold decides the system security level; a high value will give a more secure system but will also result in more false rejections, while a lower value may give additional false acceptances and hence be less secure.

Verification of input fingerprint image against stored reference fingerprint images is done by finding the Euclidean distance between the two corresponding finger codes [13,14,15]. It is highly expected that the value of Euclidean distance should be zero or as minimum as possible. Smaller value of Euclidean distance indicates closest match found and larger value indicates very low probability of finding corresponding match.

In a plane with  $p_1(x_1, y_1)$  and  $p_2(x_2, y_2)$  its Euclidean distance is  $\sqrt{(x_2 - y_2)^2 + (x_1 - y_1)^2}$ .

Matching of the fingerprint image is performed based on the minimum Euclidean distance between the input feature vector and the template feature vector.

## 4. EXPERIMENTAL RESULTS

Fingerprint images of **Db1\_a** & **Db1\_bof FVC2002** database are used for experimentation which contains a set of single reference fingerprint and its respective seven damaged fingerprints. Total 880 fingerprint images have been used for testing (8 fingerprint images of 110 persons).

In order to obtain a better result, the size of the co-occurrence matrix parameters are determined experimentally. The input images of the proposed system are first normalized to a desired level (detailed in Section 3.1.1) for reducing the dynamic range of the gray levels. Indeed, it is also justified to use a lesser number of gray levels. We used 4 gray levels to represent a co-occurrence matrix. Also, distance  $d$  is taken as 1 to capture optimum texture patterns.

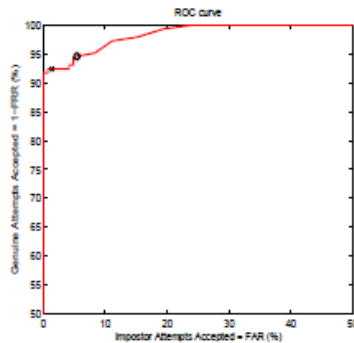
To evaluate the performance of the proposed matching method, False Acceptance Ratio (FAR) and False Rejection Ratio (FRR) are used. A Receiver Operating Characteristic (ROC) curve is issued to plot the Genuine Acceptance Rate (1-FRR) against False Acceptance Rate. To compute the False Acceptance Rate (FAR)

$$\text{FAR} = \frac{\text{Number of accepted imposter claims}}{\text{Total number of imposter accesses}} * 100$$

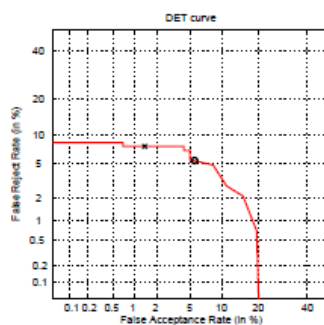
and the False Rejection Rate (FRR)

$$\text{FRR} = \frac{\text{Number of rejected genuine claims}}{\text{Total number of genuine accesses}} * 100$$

To compute genuine match score for the entire database, one fingerprint sample of each person is matched against other fingerprint samples of the same person. To compute imposter match, one fingerprint sample is matched against the remaining sample of the other persons.



(a)



(b)

**Figure.8 Performance measure plots a) Receiver Operator Curve from similarity measures with the FVC2002 database b) DET curve**

## 5. CONCLUSION

We have proposed a new GLCM based fingerprint feature extraction and Euclidean based matching method without the need to detect minutiae. In the proposed method, a reference point is established for the fingerprint. Certain area around the detected reference point is used as ROI for feature extraction. Fingerprint matching is performed based on finding the normalized Euclidean distance between the input and the template feature vectors. Experimental results validate the effectiveness of the proposed method in extracting fingerprint features and achieving good performance. To improve the verification accuracy, further study is needed with larger database of fingerprint images, and on combining with soft biometric features.

## 6. REFERENCES

- [1] S. Pankanti, S. Prabhakar, A.K. Jain, On the individuality of fingerprints, IEEE Trans. Pattern Anal. Mach. Intell. 24 (8) (2002) 1010–1025.
- [2] X. Tan and B. Bhanu, “Fingerprint matching by geneticalgorithms,” Pattern Recognition, vol. 39, no. 3, pp. 465–477, 2006.
- [3] M. Liu, X.D. Jiang, A.C. Kot, “Efficient fingerprint search based on database clustering”, Pattern Recognition 40, pp.1793 – 1803, 2007.
- [4]. Haralick, R.M., K. Shanmugam, and Lh, Dinstein, Textural Features for Image Classification, in IEEE Transactions on Systems, Man and Cybernetics. 1973. p. 610-621
- [5] R. M. Haralick, K. Shanmugan and J. Dinstein, “Textual features for image classification” IEEE Trans. Syst. Man. Cybern. Vol. SMC-3, pp. 610-621, 1973.
- [6] Gornale S.S., Humbe V., Manza R. and Kale K.V., Fingerprint image de-noising using multi-resolution analysis (MRA) through stationary wavelet transform (SWT) method ,International Journal of Knowledge Engineering, ISSN: 0976–5816, Vol. 1, Issue 1, 2010, PP- 05-14.
- [7] B. M. Mehtre, “Fingerprint image analysis for automatic identification” Machine Vision Applicat., vol. 6, pp. 124–139, 1993.
- [8] A. M. Bazen and S.H. Gerez, “An intrinsic coordinate system for fingerprint matching,” in Proc. 3rd Int. Conf. Audio- and Video-Based Biometric Person Authentication, 2001, pp. 198–204.
- [9] A. K. Jain, S. Prabhakar, H. Lin, and S. Pankanti, “Filterbank-based fingerprint matching,” IEEE Trans. Image Processing, vol. 9, pp. 846–859, May 2000.
- [10] R.C. Gonzalez, R. Woods, Digital Image Processing, Prentice Hall, 2008.
- [11] Anil Jain and Sharath Pankanti. Automated Fingerprint Identification and Imaging Systems. <http://citeseer.nj.nec.com/453622.html>
- [12] Ying Hao, Tieniu Tan and Yunhong Wang (2002). An Effective Algorithm for Fingerprint Matching. IEEE Region 10 Technical Conference on Computers, Communication, Control and Power Engineering, 2002.
- [13] Lin Hong, Yifei Wan, Anil Jain “Fingerprint Image enhancement : Algorithm and performance Evaluation “ IEEE Transaction on pattern analysis and machine Intelligence , Vol.20, No.8, August 1998.
- [14] Anil k. Jain , Salil Prabhakar, Lin Hong, Sharat Pankanti “Filterbank-Based Fingerprint Matching” , IEEE Transaction on Image Processing , Vol.9, No.5, May 2000.
- [15] T. Chang, “Texture Analysis of Digitized Fingerprints for Singularity Detection,” Proc. Fifth ICPR, pp. 478-480, 1980.