Statistical Descriptors for Fingerprint Matching

Ravinder Kumar
Ansal Institute of Technology
GGS IP University
Delhi - 110075, India

Pravin Chandra
University School of Information
Communication Technology,
GGSIPU Delhi - 110075, India

M. Hanmandlu
Department of Electrical
Engineering, IIT Delhi,
New Delhi -110016, India.

ABSTRACT
This paper presents a novel algorithm for fingerprint matching using statistical descriptors. This fingerprint-matching algorithm overcomes the problems faced during matching of low quality fingerprint images. The steps of the algorithm include extraction of core point using Poincare index method, extraction of Region of Interest (ROI) around core point, and similarity evaluation of statistical descriptors using k-NN classifier. Statistical descriptors are computed from 16 Gray Level Co-occurrence Matrices (GLCM) from Extracted ROI. The proposed algorithm is evaluated on the FVC2002 DB2 database. The experimental results show the effectiveness of proposed algorithm. Computational efficiency is improved by considering the ROI of size 101×101 around the core point.

General Terms
Fingerprint Matching, Biometrics, and Pattern classification.

Keywords
Fingerprint Identification, Statistical Descriptor, Genuine Acceptance Rate, False Acceptance Rate, Feature Extraction.

1. INTRODUCTION
With the rapid advancement in the information technology, our society becomes more and more electronically connected. In this electronically connected society automatic identification of individuals becomes highly desirable. As a result, design and development of highly accurate automatic personal identification techniques becoming more critical.

Traditionally, two major types of personal identification approaches have been widely used:

- Token-based and
- Knowledge-based

Token-based approaches use "something that you possess" to make personal identification. Individuals are identified by demonstrating that they are in possession of certain token / document, such as passport, driving license, ID card, credit card, and keys. Knowledge-based approaches use "something that you know" to make personal identification. Individuals are identified by demonstrating that they are in possession of information and knowledge, which only they are expected to know such as password and personal identification number (PIN).

The major advantages of these traditional personal identification approaches are that:

- They are very simple
- They can be easily integrated into different systems
- They have low cost.

However, since these traditional approaches are not based on any inherent attributes of an individual to make a personal identification, they have a number of disadvantages: tokens may be lost, stolen, or misplaced; PIN may be forgotten or guessed by impostors. All of these approaches are also unable to differentiate between an authorized person and an impostor who fraudulently acquires the "token" or "knowledge" of the authorized person. Therefore, they are unable to satisfy the security requirements of our electronically inter-connected information society. Biometrics refers to identifying an individual based on his or her physiological or behavioral characteristics (identifiers) [1]. It relies on "something which you are or you do" to make a positive personal identification. It is inherently more reliable and more capable than knowledge-based and token-based techniques in differentiating between an authorized person and a fraudulent impostor, because the physiological or behavioral characteristics are unique to every person. Also, the person to be identified is required to be physically present at the point of identification. Biometrics provides a solution for the security requirements of our electronically interconnected information society and has the potential to become the dominant automatic personal identification in the near future [1].

Fingerprint is probably the most popularly used biometrics for person identification because of individuality, permanence, and reliability [2]. The methods of fingerprint recognition have been roughly classified as minutiae based, and image based methods.

Minutiae – based matching is a popular and widely used technique for fingerprint matching [3, 4]. In this technique feature vector is extracted from fingerprint images. Typical feature vector consists of minutiae characteristics like type (ridge bifurcation or ridge ending), position (x, y coordinates), orientation (angle formed between ridge direction and x-axis) etc. This matching essentially consists of alignment of template and the input minutiae set to determine the total number of matched minutiae. Performance of minutiae based methods are highly depends upon quality of fingerprint images. In low quality images these methods results in low matching rate, because these methods does not utilize the rich discriminatory information available in fingerprint images [5].

Image based methods are relatively having high computational complexity, but perform better as compared to minutiae based techniques in low quality images [5, 6, 7, 8]. These methods use features orientation ridge pattern, and texture information etc. The performance of image-based methods is heavily depends on the alignment, translation and scaling.

Arivazhagan et al. [9] proposed fingerprint verification methods by using gabor wavelets and co-occurrence metrics, whereas Yazdi et al. [10] had classifies fingerprint images by employing co-occurrence metrics. These works motivates us to propose a fingerprint matching methods based on extracting statistical descriptors computed from co-occurrences metrics.

This paper proposes a fingerprint-matching algorithm using the four statistical descriptor characterized by the co-occurrence matrix. The proposed method assumes that tone and texture are always present in an image. The steps involved in this algorithm include: Fingerprint image enhancement, Core point detection, Alignment by rotation to have zero orientation, Region of Interest (ROI) extraction, and finally computing the GLCM (Gray Level Co-occurrence Matrices) to extract statistical features. This proposed method has advantage over previous methods as it includes two additional techniques: Extraction of region of interest to minimize computational efforts, and analysis fingerprint image based on statistical descriptor.

This paper is organized in the following manner: Section 2 describes the proposed algorithm. Section 3 discusses Gray-Level Co-occurrence Matrix and proposed feature extraction. Section 4 highlights the experimental results. And finally, the section 5 concludes the paper.

1. PROPOSED ALGORITHM

The proposed algorithm for fingerprint matching consists of following five steps and is shown in Fig. 1.

Algorithm:

Step 1: Fingerprint Acquisition

Step 2: Fingerprint image enhancement

Step3: Alignment of fingerprint using Maximization of Orientation correlation

Step 4: Region of Interest (ROI) extraction

Step 5: Extraction of Statistical Descriptor

Step 6: Training and similarity measure using k-NN classifier

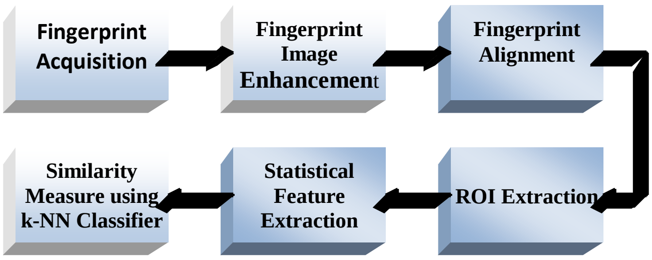

Fig. 1: Flowchart for Proposed Algorithm for Fingerprint Matching

1.1 Fingerprint Image Enhancement

Fingerprint enhancement is a very important preprocessing step for any Automatic fingerprint identification system [5]. The performance of a feature extraction algorithm heavily depends on the quality of the input fingerprint images. The fingerprint enhancement method proposed by Hong, Wan and Jain [11] is used here with different modified ridge filter to increase the contrast between ridge and valley [12]. The enhanced fingerprint image is shown in Fig. 2.

Fig. 2. (a) Typical Fingerprint image and (b) Enhanced image

1.2 Fingerprint Alignment

Maximizing the correlation between test image and template image computed over orientation field performs fingerprint alignment. The template images are rotated at various angles in steps using equation (1). The maximum value of correlation will provide the angle of rotation θ. In this way all the test images are pre-aligned and preprocessed before matching.

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \qquad (1)$$

1.3 ROI Extraction

To speed up the matching process, test and template fingerprint images are cropped of size 101×101(m×n) around core point and this considered as the region of interest (ROI) for computing statistical descriptor. The cropped image is shown in Fig. 3 [13].

Fig. 3. Cropped image around core point

2. STATISTICAL DESCRIPTOR

A statistical method of examining texture considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

The GLCM is a statistical approach, which describes second-order statistics of a texture image. GLCM is a two-dimensional histogram in which the $(i, j)^{th}$ element is the frequency that event i co-occurs with event j. It is specified by relative frequencies $P(i, j, d, \theta)$ in which two pixels, separated by distance d, occur in direction specified by θ, one with gray level i and the other with gray level j as shown in Fig. 4.

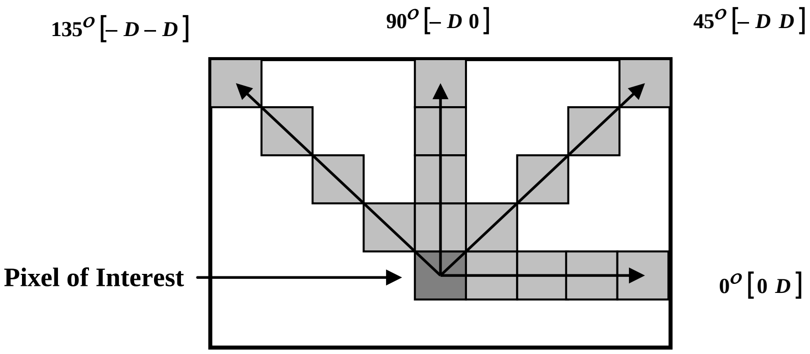

Fig. 4. Various directions and pixel of interest

2.1 Texture Feature Extraction

It is assumed that all the texture information is contained in gray scale co-occurrence matrices. A single GLCM is not sufficient to describe the all the features. For example, single horizontal spatial relationship might not be sensitive to texture with a vertical orientation. Therefore, multiple GLCM are computed for four directions specified by an angle 0^o, 45^o, 90^o, 135^o for, and a relative distance of one to four pixels. In all we have computed 16 GLCM in four directions with relative distance varying from one to four. Haralick et al. [14] defines the measures of 14 different textural features, which can be extracted from these co-occurrence matrices. We have used four features, which can successfully characterize the statistical behavior of GLCM given below [15].

Correlation $$\sum_{i=1}^{K}\sum_{j=1}^{K}\frac{(i-m_r)(j-m_c)p_{ij}}{\sigma_r\sigma_c} \quad (2)$$

Contrast $$\sum_{i=1}^{K}\sum_{j=1}^{K}(i-j)^2 p_{ij} \quad (3)$$

Entropy $$-\sum_{i=1}^{K}\sum_{j=1}^{K}p_{ij}\log_2 p_{ij} \quad (4)$$

Uniformity $$\sum_{i=1}^{K}\sum_{j=1}^{K}p_{ij}^2 \quad (5)$$

The quantities used in the above descriptors are defined as follows:

$$m_r=\sum_{i=1}^{K}i\sum_{j=1}^{K}p_{ij}$$

$$m_c=\sum_{i=1}^{K}j\sum_{j=1}^{K}p_{ij}$$

$$\sigma_r^2=\sum_{i=1}^{K}(i-m_r)^2\sum_{j=1}^{K}p_{ij}$$

$$\sigma_c^2=\sum_{i=1}^{K}(j-m_c)^2\sum_{j=1}^{K}p_{ij}$$

Where m_r , m_c are means and σ_r , σ_c are the standard deviations computed along rows and columns respectively.

3. Experimental Results and Discussion

The proposed algorithm is evaluated on Fingerprint Verification Competition (FVC2002) database [16]. The matching performance has been evaluated in terms of Equal Error Rate (EER) computed using equation (6)[17]. Total fingerprints used in this experiment are 800, which includes 100 different fingers with 8 images from each finger. We have used the k-NN classifier to measure the similarity [18]. Six out of eight fingerprints are used for training and remaining two are set aside for testing. In all 600 fingerprint are used for training and 200 fingerprints are used for testing

$$EER=\frac{FAR+FRR}{2}, where$$
$$FAR=\frac{Numberof\ imposterclaimsaccepted}{Totalnumberof\ imposterclaims}\times 100, \quad (6)$$
$$FRR=\frac{Numberof\ gunuineclaimsrejected}{Totalnumberof\ gunuineclaims}\times 100$$

Experiments have been conducted for each datasets.

The test results of the experiment have been summarizes in Table 1.

Table 1. The FAR (%) and FER (%) for FVC 2002 database with k-NN Classifier

	DB1_a	DB2_a	DB3_a	DB4_B_a
FAR	2.6	3.6	3.8	2.5
ERR	2.2	2.6	3.0	1.5

Table 2. Shows the comparison of results from the proposed method with the results obtained from methods proposed by Yang et al. [17] using tessellated invariant moment feature, Ross et al. [19] using minutiae along with ridge map features, Jin et al. [20] using integrated wavelet and Fourier-Mellin invariant framework with four multiple training WFMT feature, and Amornraksa et al. [21] using DCT feature.

Table 2. Comparison between EER (%age) obtained from different matchers and proposed method on FVC2002 database.

Method	DB1_a	DB2_a	DB3_a	DB4_a	Average
Yang et al. [17]	1.63	3.78	4.20	4.68	3.57
Ross et al.[18]	1.87	3.98	4.64	6.21	4.17
Jin et al. [19]	2.43	4.41	5.18	6.62	4.66
Amornraska et al.[20]	2.96	5.42	6.79	7.53	5.68
Proposed	2.4	**3.1**	**3.4**	**2.0**	**2.72**

It is proved from the above table that the proposed algorithm has better performance in terms of matching accuracy as compared to other four prominent methods. The proposed method has achieved the average EER of 2.72%, while the best EER of other methods is 3.57 %.

4. CONCLUSION

This paper proposes a novel method for fingerprint identification using GLCM to compute statistical descriptors. We have used 16 co-occurrence matrices to computed four statistical descriptors. The experimental results verified the acceptability of the proposed descriptor. To speed up the process, we have extracted the region of interest (ROI) around core point. The result shows that the performance of this method is better than the other methods proposed in the literature as well as minutiae based method. The only drawback of this method is, it can only be applied to the images having core point. For future research, this proposed method can be combined with minutiae based method to obtain a hybrid algorithm to further enhance the performance.

5. ACKNOWLEDGMENTS

Our thanks to those who have contributed directly or indirectly in the development of this paper.

6. REFERENCES

[1] Jain, A.K., Ross, A., Prabhakar, S.: An introduction to biometric recognition. IEEE Transactions on Circuits and Systems for Video Technology 14(3), 4–20 (2004)

[2] Wayman, J.L.: Fundamentals of biometric authentication technologies. Int. J. Image Graphics 1(1), 93–113 (2001)

[3] A.K. Jain, L. Hong, S. Pankanti, R. Bolle, An identity—authentication system using fingerprints, Proc. IEEE 85 (9) (1997) 1365–1388.

[4] J. Liu, Z. Huang, K. Chan, Direct minutiae extraction from gray-level fingerprint image by relationship examination, in: International Conference on Image Processing, vol. 2, 2000, pp. 427–430.

[5] Maltoni, D., Maio, D., Jain, A.K., Prabhakar, S.: Handbook of Fingerprint Recognition. Springer (June 2009)

[6] Ling Hong, Yifei Wan, and Anil Jain, “Fingerprint Image Enhancement: Algorithm and Performance Evaluation”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, no. 8, August 1998.

[7] A.K. Jain, S. Prabhakar, L. Hong, S. Pankanti, Filterbank-based fingerprint matching, IEEE Trans. Image Process. 9 (5) (2000) 846–859.

[8] Sha L. F. Zhao F. Tang X. O.: Improved fingercode for filterbank-based fingerprint matching, International Conference on Image Processing Vol. 2, 2003, pp. 895-898.

[9] Arivazhagan, S., AruIFiora, T.G., Ganesan, L.: Fingerprint Verification using Gabor Cooccurrence Features. In: International Conference on Computational Intelligence and Multimedia Applications, pp. 281–285 (2007).

[10] Yazdi, M., Gheysari, K.: A New Approach for the Fingerprint Classification Based on Gray-Level Co-Occurrence Matrix. International Journal of Computer and Information Science and Engineering (2008)

[11] Jain, A.K., Prabhakar, S., Pankanti, S.: Filterbank – based fingerprint matching. IEEE Transactions on Image Processing 9, 846–859 (2000)

[12] Ravichandran, G., Casasent, D.: Advanced in-plane rotation-invariant correlation filters. IEEE Transactions on Pattern Analysis and Machine Intelligence 16(4), 415–420 (1994)

[13] Kumar, R., Chandra, P., Hanmandlu, and M.: Fingerprint Matching Based on Orientation Feature. Advanced Materials Research Journal 403-408, 888–894 (2011), doi:10.4028/www.scientific.net/AMR.403-408.888.

[14] Haralick, R.M., Shanmugam, K., Dinstein, I.H.: Textural Features for Image Classification. IEEE Transactions on Systems, Man and Cybernetics 3, 610–621 (1973)

[15] Aggarwal, G., Ratha, N.K., Jea, T.-Y., Bolle, R.M.: Gradient based textural characterization of fingerprints. In: Proceedings of IEEE International Conference on Biometrics: Theory, Applications and Systems (September-October 2008)

[16] D Maio, D Maltoni, R Cappelli, J.L. Wayman, and A.K. Jain, FVC2000: Fingerprint Verification Competition, IEEE Trans. Pattern Analysis Machine Intelligence, 24(3), 402-412 (2002).

[17] Yang J.C., Park D.S.: A fingerprint verification algorithm using tessellated invariant moment features, Neurocomputing 71 (2008) 1939 – 1946.

[18] R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classification, second ed., Wiley, 2000.

[19] Ross A. Jain A. K. Reisman J, A hybrid fingerprint matcher, Pattern Recognition 36(7) (2003) 1661-1673.

[20] Jin A.T.B., Ling D.N.C., Song O.T., An efficient fingerprint verification system using integrated wavelet and Fourier-Mellin invariant transform, Image Vis. Comput. 22 (6) (2004) 503–513.

[21] T. Amornraksa, S. Tachaphetpiboon, Fingerprint recognition using DCT features, Electron. Lett. 42 (9) (2006) 522–523.