A New Approach for the Fingerprint Classification Based on Gray-Level Co-Occurrence Matrix

Mehran Yazdi, and Kazem Gheysari

***Abstract*—**In this paper, we propose an approach for the classification of fingerprint databases. It is based on the fact that a fingerprint image is composed of regular texture regions that can be successfully represented by co-occurrence matrices. So, we first extract the features based on certain characteristics of the co-occurrence matrix and then we use these features to train a neural network for classifying fingerprints into four common classes. The obtained results compared with the existing approaches demonstrate the superior performance of our proposed approach.

***Keywords*—**Biometrics, fingerprint classification, gray level co-occurrence matrix, regular texture representation.

I. INTRODUCTION

A common and reliable biometric for automatic personal identification is fingerprint. Indeed, due to their uniqueness and unchangeability, fingerprints have widely used by many police agencies as a trusted biometric for personal identification. However, the fingerprint recognition that aims to find a match for a probe fingerprint in the database of enrolled prints is extremely long because of an enormous number of personal records in the database (e.g. there are more than millions of US`s criminal records). Classification can help to accelerate the fingerprint recognition. An automatic fingerprint classification method aims to enhance the fingerprint images, to identify appropriate features, to extract these features and finally to classify the fingerprints based on these features. Consequently, the time for the matching task is significantly reduced. This is the reason why many agencies use classification methods to reduce the size of the search space to the fingerprints of the same category before matching. Nowadays, the automatic fingerprint classification has become a routinely predominant process for personal identification and consequently should be reliable, does not create overlapping classes and processes each fingerprint in a short time.

The first attempts to classify the fingerprints were made by Galton [1] and Henry [2]. Galton originally proposed the use of three major finger print classes: the arch, the whorl and the loop. Henry changed the Galton`s classification and defined eight classes: whorl, Plain Arch, Right Loop, Left Loop, Central Pocket, Tented Arch, Twin Loop, and Accident.

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However, left loops, right loops and whorls are the most popular types and nearly 94% of fingerprints are in these classes [3]. So, we believe that four classes of left loop, right loop, whorl and arch are the major classes for fingerprint classification. Fig. 1 shows an example of four classes.

Arch Whorl Right Loop Left Loop

Fig. 1 Four major fingerprint classes

II. PREVIOUS WORKS

Many approaches to automatic fingerprint classification have been presented in the literature and the research on this topic is still very active [3]. The approaches are mostly based on two main features in a fingerprint: 1) Global ridge and furrow structures that form special patterns in the central region of the fingerprint. 2) Local ridge and furrow minute details. Usually, a fingerprint is classified based on the first type of features and is uniquely identified based on the second type of features (ridge endings and bifurcations, also know a as minutiae). One advantage of this framework is that the ridge structures can be global features, and therefore can often be reliably extracted from images even in presence of hard noise.

There are two main approaches for extracting information about fingerprint ridge structures. One method is based on developing a mathematical model of fingerprint ridges and representing the fingerprint using these models. Another approach uses record characteristics of the ridges and stores this information for classification.

Recently, some papers have reported very good results in the automatic classification of fingerprint databases. Jain et al. used the Gabor filter in four directions to extract features from fingerprints for classification [4]. In another attempt, they have stored the shape information about the structure of fingerprint ridges for their classification scheme [5]. Each ridge is classified as either nonrecurring, recurring, or fully recurring. They obtained an 94.8% correct classification. Jain and Minut [6] have proposed a mathematical model for each fingerprint class that represents the ridge structure of fingerprints belonging to that class. They obtained an 91.3% correct classification. Chang and Fan have developed an alternate fingerprint representation that captures structural information [7]. They obtained an 94.8% correct classification. Yao et al. [8] have developed an algorithm based on support vector machines. They obtained an 94.7% correct classification.

We propose a new approach for the fingerprint classification based on the fact that a fingerprint image is composed of regular texture regions that can be successfully represented by co-occurrence matrices. We first apply a histogram equalization for reducing the influence of the noise in fingerprint images. Then, a series of simple morphological operations will be applied to emphasize the ridge structure of fingerprint patterns. The texture context of fingerprint structure will be represented by co-occurrence matrices that specify the relation of neighbor pixels in certain distance in a given direction. Based on the applied co-occurrence matrices, some features are defined and extracted. Finally a classifier based on neural network will be trained and used for classify the fingerprint databases on four major classes.

III. Histogram Equalization

Because there are many noises in original fingerprint image, an image enhancement algorithm such as histogram equalization is usually applied to reduce the influence of the noise in fingerprint image and to emphasize the ridges structure of fingerprint patterns. Fig. 2 shows the result of applying histogram equalization on a fingerprint image.

(a) (b)

Fig. 2 Result of histogram equalization: (a): original image (b): After histogram equalization

IV. Gray-Level Co-Occurrence Matrix (GLCM)

A statistical approach that can well describe second-order statistics of a texture image is a co-occurrence matrix. Gray level co-occurrence matrix (GLCM) was firstly introduced by Haralick [9] [10]. A gray-level co-occurrence matrix (GLCM) is essentially a two-dimensional histogram in which the (i, j)th element is the frequency of 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 the angle θ, one with gray level i and the other with gray level j. A co-occurrence matrix is therefore a function of distance r, angle θ and grayscales i and j.

Our observation is that a fingerprint image can be decomposed into regions with regular textures. So we should be able to represent these regular texture regions by using co-occurrence matrices. To do so, we utilize the co-occurrence matrices in angles of 0°, 45°, 90°, and 135° as follows [9]:

$$\begin{aligned} P(i,j,d,0) = \#\{((k,l),(m,n)) \in (L_r \times L_c)\times(L_r \times L_c) \\ k-m=0, |I-n| = d, I(k,l)-i, I(m,n)=j\} \end{aligned} \quad (1)$$

$$\begin{aligned} P(i,j,d,45) = \#\{((k,l),(m,n)) \in (L_r \times L_c)\times(L_r \times L_c) \\ (k-m=d, |I-n| = -d) or (k-m=-d, |I-n| = d) \\ I(k,l)=i, I(m,n)=j\} \end{aligned} \quad (2)$$

$$\begin{aligned} P(i,j,d,90) = \#\{((k,l),(m,n)) \in (L_r \times L_c)\times(L_r \times L_c) \\ k-m=d, |I-n| = 0, I(k,l)=i, I(m,n)=j\} \end{aligned} \quad (3)$$

$$\begin{aligned} P(i,j,d,135) = \#\{((k,l),(m,n)) \in (L_r \times L_c)\times(L_r \times L_c) \\ (k-m=d, |I-n| = d) or (k-m=-d, |I-n| = -d) \\ I(k,l)=i, I(m,n)=j\} \end{aligned} \quad (4)$$

V. Normalization

This part of algorithm has significant effect on total performance of algorithm. The problem is that the total number of compared pixels pairs is different due to the angular relationships. Moreover, the size of images in the databases is not the same. To overcome these problems, it is necessary to normalize the co-occurrence matrices [9][11]. We used the normalized correlation algorithm proposed by Kim *et al.* [11] to normalize all co-occurrence matrices.

VI. Feature Extraction

We compute GLCM for the fixed d, and θ=0˚, 45˚, 90˚, and 135˚. So we have 4 co-occurrence matrices. Based on each computed GLCM, 12 features that can successfully characterize the statistical behaviour of a co-occurrence matrix are extracted. They are as follows:

1) Maximum probability: $f_1 = \underset{i,j}{Max}\, p(i,j)$

2) Contrast: $f_2 = \sum_i \sum_j (i-j)^2 p(i,j)$

3) Entropy $f_3 = \sum_i \sum_j \left(\frac{p(i,j)}{\log p(i,j)} \right)$

4) Angular Second Moment: $f_4 = \sum_i \sum_j p(i,j)^2$

5) Homogeneity $f_5 = \sum_i \sum_j \left(\frac{p(i,j)}{1+|i-j|} \right)$

6) Dissimilarity $$f_6 = \sum_i \sum_j |i-j| p(i,j)$$

7) Mean $$f_7 = \frac{\sum_i \sum_j p(i,j)}{m \times n}$$

where m and n are the number of rows and columns in p respectively.

8) Correlation $$f_8 = \sum_i \sum_j \frac{(i-\mu_x)(j-\mu_y)p(i,j)}{\sigma_x \sigma_y}$$

where μ_x, μ_y are means and σ_x, σ_y are the standard deviations of p_x and p_y respectively.

If we define $S = \sum_i \sum_j p(i,j)$, we can extract 4 other features as follows:

9) $$f_9 = \frac{\sum_i \sum_j \frac{p(i,j)}{j2}}{S}$$ 10) $$f_{10} = \frac{\sum_i \sum_j j^2 p(i,j)}{S}$$

11) $$f_{11} = \frac{\sum_i \left(\sum_j p(i,j) \right)^2}{S}$$ 12) $$f_{12} = \frac{\sum_j \left(\sum_i p(i,j) \right)^2}{S}$$

VII. CLASSIFIER

For the classification task, an artificial feed-forward neural network with two hidden layers is used. This neural network has 48 input neurons (12 features multiplied by 4 co-occurrence matrices) and 4 output neurons corresponding to 4 classes of arch, whorl, right loop and left loop. The number of neurons in hidden layers is determined experimentally.

VIII. EXPERIMENTAL RESULTS

To test the proposed approach, two databases were used. One famous database containing FVC2000 [12], FVC2002 [13], and FVC2004 [14] from Biometric System Laboratory University of Bologna and other from Neurotechnologija web site [15] named VeriFinger_Sample_DB. From these databases, 730 fingerprint images were classified in four classes, 169 images from arch class, 140 images from whorl class, 222 images from right loop class, and 199 images from left loop class. We selected randomly 365 images from four classes to train our neural network. The resting 365 images were used to test the classifier. Table I summarizes the results for different number of neurons in second and third hidden layers. As we can see, the neural network with 23 neurons for the second layer and 8 neurons for the third layer correctly classifies images in 99.02% with no misclassification. Note that the neural network either finds a class for a given fingerprint image or announces that the image belongs to none of the classes. So, for the 0.98% of images, no class has been found. We should mention that this table was obtained by selecting the size of co-occurrence matrices (N) equals 64 and pixel separation distance (d) equals 2. Table II shows the performance of the algorithm for different values of N and d. As can be seen, for N=64 and d=2, we have obtained better performance. It is obvious that when d is small, we cannot exploit the pattern structure of pixels in the co-occurrence matrix. In contrary, when d is grand, there is no enough pattern structure between pixels that are far from each other.

In order to test the robustness of the proposed algorithm with respect to noise image, we added "salt & pepper" noise to the test images. Fig. 3 shows the performance of the algorithm for different fingerprint classes. As we can see, the best and the worst robustness is related to Arch and Left Loop classes, respectively. The resting two classes have close robustness to Arch class. Our observation from the used databases was that the Left Loop fingerprint images were low quality related to other classes and more sensitive to noise.

IX. CONCLUSION

We have proposed a new approach for the fingerprint classification based on the co-occurrence matrix. The features extracted from co-occurrence matrices can well characterize the regular texture of fingerprint images. The obtained results demonstrated the superior performance of our proposed approach related to recent reports (Table III).

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TABLE I
PERFORMANCE OF THE ALGORITHM FOR THE DIFFERENT NUMBER OF NEURONS IN SECOND AND THIRD HIDDEN LAYERS OF THE NEURAL NETWORK (D=2, N=64)

Number of neurons for second hidden layer	*Number of neurons for third hidden Layer*	*Overall correctly classified*	*Overall Misclassified*
8	8	96.1	1
10	8	93.4	1
16	8	97.85	0
20	8	98.77	0
22	8	96.22	0
23	8	**99.02**	0
25	8	93.85	0
10	10	96.2	1
12	10	89.65	1
16	10	88.42	0

TABLE II
PERFORMANCE OF THE ALGORITHM FOR THE DIFFERENT VALUES OF N AND D

N(size of GLCM)	*d (distance from origin)*	*Overall correctly classified*	*Overall Misclassified*
256	1	97.41	0
192	1	94.94	1
128	1	94.81	2
64	1	97.96	0
256	2	95.35	2
192	2	95.7	0
128	2	93.32	0
64	2	**99.02**	0

TABLE III
A COMPARISON OF RECENT FINGERPRINT CLASSIFICATION ALGORITHM ACCURACIES [3] WITH OUR ALGORITHM

Author and year	Classes	Accuracy
Wilson et al. (1992)	5	**81.0**
Karu and Jain (1996)	5	**85.4**
Jain et al. (1999)	5	**90.0**
Hong and Jain (1999)	5	**87.5**
Cappelli et al. (1999)	5	**92.2**
Cappelli et al. (1999)	5	**87.1**
Yao et al. (2001)	5	**89.3**
Chang and Fan (2002)	5	**94.8**
Mohamed and Nyongesa(2002)	5	**92.4**
Zhang et al. (2002)	5	**84.0**
Yao et al. (2003)	5	**90.0**
Wilson et al. (1992)	4	**86.0**
Karu and Jain (1996)	4	**91.4**
Senior (1998)	4	**81.6**
Jain et al. (1999)	4	**94.8**
Hong and Jain (1999)	4	**92.3**
Senoir (2001)	4	**88.5**
Jain and Minut (2002)	4	**91.3**
Yao et al. (2003)	4	**94.7**
Our method	**4**	99.02

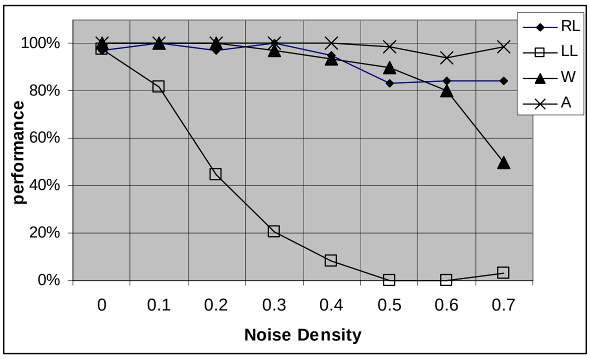

Fig. 3 Performance of the algorithm related to different values for noise density (N=256,d=1). RL stands for right loop, LL stands for left loop, W stands for whorl, and A stands for arch