

A New and Effective Method in Fingerprint Classification

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Abstract: Nowadays using fingerprint as a biometric feature is widely utilized in related applications of individuals' identification. Reliability, cost-effectiveness and its applicability in comparison to the other biometric IDs including signature, iris identification, face identification and motion identification, has led to the widespread use of fingerprint in different applications. If too much data is in hand fingerprint classification is one of the ways to reduce the time of searching and identifying an unknown image in a great set of images. In this paper a new method for classifying fingerprints in databases FVC 2000, FVC 2002 and FVC 2004 is presented. In order to extract features from fingerprint images we used co-occurrence matrix and in order to classifying and identifying individuals we used a neural network. The used neural network was a multilayer perceptron network with training after error propagation method.

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1. Introduction

Regarding individuals' identification and due applications, lots of researchers have tried to find methods with high accuracy and low cost in order to reach such an end. The fingerprints due to its specific features like inalterability, its uniqueness, capability of being classified and non-aggressiveness has a special place. An individual's fingerprint is unique and inalterable during his life. Fingerprint has lots of applications and recognizing it for a researcher when the bulk of data is too much will be time consuming. So classifying fingerprints will be so helpful in this regard to do the job in a shorter time span. In fact, classifying reduces the search area and results in increasing the pace of our search system. Meanwhile nowadays identifying people by their fingerprints is a usual trend and should be done in the least possible time. A typical scheme of biometric matching systems is shown in Figure 1.

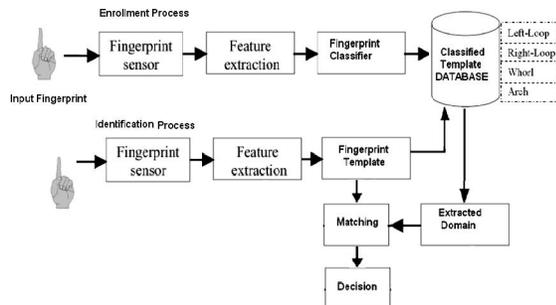


Figure 1. Block diagram of a typical Automatic Fingerprint Verification system [15].

Fingerprint images are composed of a set of black lines. These black lines are the traces of skin grooves on fingers and leave such traces because of being

stained by ink. Each of these black lines is called ridge and the white space between two ridges is called furrow. The way ridges and furrows are arranged results in different patterns; based on such patterns these images are placed in different classes. Figure 2 illustrates some fingerprint images in different classes.

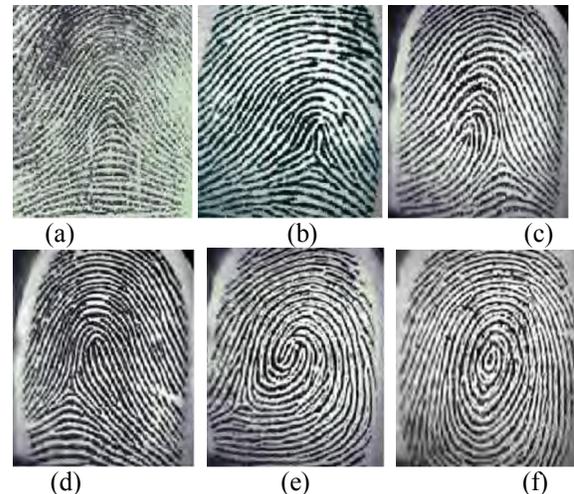


Figure 2: a sample of some fingerprint images in 6 classes; (a) plain arc, (b) tented arc, (c) left loop, (d) right loop, (e) plain loop, (f) double loop whorl.

However, Arch, whorls, right loops and left loops are the most popular types and nearly 94% of fingerprints are in these classes [16]. So, we used four classes of arch, whorl, right loop and left loop for fingerprint classification.

In addition to these general patterns, two other categories of features are shaped by ridges and furrows; a-singular points which include core point and delta point. b-minutiae features which the most

important ones are bifurcation and endpoint. Figure 3 shows a sample of singular points and Minutiae features in a fingerprint image.

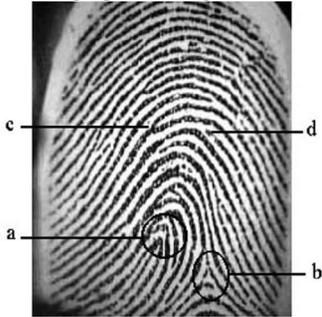


Figure 3: shows a sample of singular points and Minutiae features in a fingerprint image. a- core point b- delta point c- bifurcation feature and d- endpoint feature.

There are lots of different methods to automatic classification of fingerprints. These methods can be divided into four general categories;

- 1- Model-based classification
- 2- Structure-based classification
- 3- Syntactic classification
- 4- Hybrid classification

In model-based classification method, singular points are detected on the image and according to the number of singular points and their location to one another classification takes place [1]. In structure-based classification the ridges in fingerprint images are locally used to classify the images [2-5]. The accuracy rate in reported classification for [2] to classify 5 classes was 90% (with 18% disapproval) and for [3] to classify 4 classes was 91.5%. In syntactic classification a grammar is used for fingerprints substitution and consequently their classification [6, 7]. In hybrid classification methods, a combination of two mentioned methods is used as a criterion for classification [8, 10]. The best reported accuracy for [8] was 95.6% (with 20% disapproval) in classifying 5 classes.

In this paper a new method for feature extraction based on the existing information on the frequency spectrum of the image has been presented.

In this method feature extraction is done by means of co-occurrence matrix of spectrum. In proposed method there is no need to detect singular points and define local ridges in the image. The steps towards image classification and proposed algorithm can be summarized in the following 4 steps;

- 1- Producing the frequency spectrum of the fingerprint image
- 2- Applying designed co-occurrence matrix on the spectrum
- 3- Extracting feature from co-occurrence matrix and producing characteristic vector

- 4- Classifying characteristic vectors by means of neural networks

In section 2 the way of feature extraction will be explained. In section 3 the neural network classifiers will be introduced. In section 4 the results of the fingerprint images' classification FVC2000 [12], FVC 2002 [13] and the proposed algorithm is described. Results and discussions on this research will be presented in final section.

2. Feature extraction

In the proposed method, feature extraction is done in frequency spectrum and by means of frequency spectrum of the fingerprint image. In this method co-occurrence matrix with a specific structure is used in order to do feature extraction in image's amplitude spectrum. To do so first without any preprocessing, the two-dimensional Fourier transform is applied. Two-dimensional Fourier transform is defined as following:

$$F(u, v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(\frac{ux}{M} + \frac{vy}{N})} \quad (1)$$

$$u = 0, 1, \dots, M-1; \quad v = 0, 1, \dots, N-1$$

In above equation $f(x, y)$ is image matrix and N, M is image dimensions. $F(u, v)$ is Fourier transform in two dimensions of u, v that u is the frequency along image's x axis and v is the frequency along the y axis. Two-dimensional Fourier transform of an image, produces a matrix in the size of image's matrix which has the information about the amplitude and phase of the fingerprint image. Amplitude spectrum and two-dimensional Fourier transform phase can be calculated from the following two equations:

$$|F(u, v)| = [R^2(u, v) + I^2(u, v)]^{\frac{1}{2}} \quad (2)$$

$$\Phi(u, v) = \tan^{-1} \left[\frac{I(u, v)}{R(u, v)} \right] \quad (3)$$

In above two equations $R(u, v)$ and $I(u, v)$ accordingly are the real and fake parts of two-dimensional Fourier transform and $|F(u, v)|$ is the amplitude spectrum and $\Phi(u, v)$ is the image's phase spectrum. To use the amplitude information the frequency amplitude must be produced. Image spectrum is symmetric around the center of the spectrum which is natural in the case of real signals. This feature of the spectrum is used to reduce the bulk of extracted features from the image.

One of the well-known tools for second-order statistics extraction from tissue images is co-occurrence matrix. In this method image is transformed into a two-dimensional matrix which each of its adjacent elements indicates the probability of locating color intensity i and j with distance of d

and an angle with the size of θ . Finally using the functions defined on this matrix some characteristics are extracted and by comparing them classification is done.

In co-occurrence matrix the more the values of image pixels are closer to each other, the more the concentration created on the core diameter of matrix is. The advantage of implementing this matrix on image's simple histogram is that in comparison to simple histogram in which the location of the pixels are disappeared and just the frequency of the pixel values are calculated, in this matrix the location of the pixels are taken into account. The greater the distribution of gray pixels, the more variance is seen in the matrix.

According to mathematical definitions a co-occurrence matrix C_k for a matrix with distance of $(\Delta x, \Delta y)$ is defined as equation 4:

$$C_k(i, j) = \sum_{p=1}^n \sum_{q=1}^m \begin{cases} 1, & \text{if } I(p, q) = i \text{ and} \\ & I(p + \Delta x, q + \Delta y) = j \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The (i, j) element of C_k matrix is the total number of i and j occurrences which stand in $(\Delta x, \Delta y)$ distance. In fact co-occurrence matrix is based on the quadratic estimation of the probability density function. Second order statistical properties may well define the whole structure of the image. Since natural images generally have low-pass feature and adjacent pixels have more solidarity the co-occurrence matrix of pixels or their coefficients are distributed diagonally. In other words the values on core diameter are big values and reduce gradually on minor diameters. After insertion act due to the reduction of solidarity the great concentration on the core diameter of co-occurrence matrix is reduced and distribution occurs on it.

Four usual features of co-occurrence matrix are; entropy, energy, contrast and homogeneity. For $C_{m \times n}$ co-occurrence matrix, related formulas regarding these features are mentioned;

1- Energy;

$$Energy = \sum_{i=1}^n \sum_{j=1}^m C_{ij}^2 \quad (5)$$

2- Entropy

$$Entropy = - \sum_{i=1}^n \sum_{j=1}^m C_{ij} \log C_{ij} \quad (6)$$

3- Contrast

$$Contrast = \sum_{i=1}^n \sum_{j=1}^m |i - j| C_{ij}^2 \quad (7)$$

4- Solidarity

$$Correlation = \frac{\sum_{ij} (i - \mu)(j - \mu) C_{ij}}{\sqrt{\text{var}(i) \text{var}(j)}} \quad (8)$$

Energy feature represents the rate of image regularity which means if the elements of image have the same shape the energy would be low. Entropy indicates the rate of disorder and randomness in image pixels; it means if the image is disordered and irregular the image entropy is great. Contrast feature indicates the rate of pixels' value changes. So, if gray levels in each even pixel are the same it is expected that the contrast value be the lowest value. Solidarity shows the linear dependence of the gray levels of adjacent pixels.

3. Classification by means of artificial neural networks

One of the most widely used classifiers is neural networks' classifiers which have many applications in pattern detection. Classifying the extracted features is done by means of several neural networks which have been specialized in the field of classification. For this purpose the multilayer perceptron, probabilistic, radial basis function and learning vector quantization networks were used. In all the said networks the number of input and output neurons was accordingly equal to the number of characteristic vector's elements and the number of image classification classes. Except these two parameters, there are other parameters which should be specified for each of the networks.

To do classification by means of MLP network, regarding the complexity of the issue a three-layer network with back propagation error learning algorithm is used. There is no specific rule to determine the number of neurons in intermediate layer of this network and the trial and error method is used to determine the optimum number of neurons. For this purpose it is necessary to evaluate the network performance for different numbers of neurons in the intermediate layer. Figure 4 shows the general structure and neural network performance.

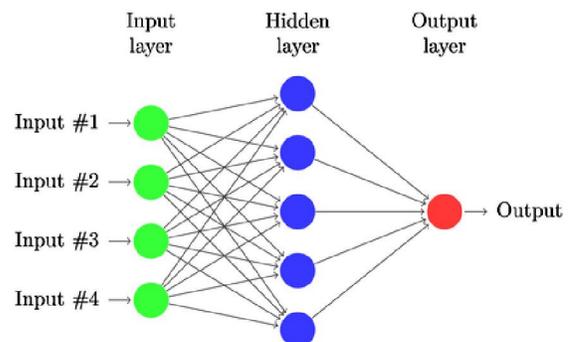


Figure 4: the structure of neural network used in this thesis

PNN network is a three layer network which its second layer is a radial basis function layer. This layer delivers the distance between the input vector and weight vector as a digit to the third layer. The third layer (competitive layer) also produces the output for the network. In the second layer of this network, to specify the distance between input vector and weight vector a Gaussian function is used. The value of σ is determined by input patterns. There is no specific rule for determining its optimum value and the optimum value of σ is determined by trial and error method. To do so network's performance is evaluated for different values of σ .

RBP network just like the PNN network is a three layer network which its second layer is a radial basis function layer. This layer delivers the distance between the input vector and weight vector as a digit to the third layer. The third layer in RBF network unlike the PNN network is a linear layer. In this network like PNN we should determine the σ parameter in Gaussian function of the second layer. For this purpose network's performance is evaluated for different values of σ .

4. Results and discussion

For evaluating the proposed algorithm for classifying the fingerprint images the standard set of FVC2004, FVC 2002 and FVC 2000 images were used. From all 600 images in hand 60% of them are used to networks' learning and 40% are used to test networks. Using the algorithm described in section 2, the images of feature extraction are used and by means of the neural networks described in section 3 the classification takes place for 4 class. As it was mentioned in the previous section in order to use MLP network it is necessary to determine the number of optimum neurons in the intermediate layer. For this purpose the performance of MLP network for the number of different neurons in the intermediate layer for classifying 4 classes is illustrated in table 1.

Table 1: Performance of the algorithm for the different number of neurons in second and third hidden layers of the MLP neural network.

Number of Neurons for second hidden layer	Number of neurons for third hidden Layer	Accuracy
6	10	95.2
9	8	92.5
15	6	96.96
19	6	96.89
23	8	95.25
20	8	97.85
22	10	92.91
18	10	95.5

MLP network with 28 neurons in their intermediate layer have the most classification accuracy value. Similarly to detect the optimum value of σ in PNN and RBF networks, related diagram for PNN and RBF networks' performance for different values of σ in the second layer for classification of 4 classes is illustrated in table 2.

Table 2: Performance of PNN and RBF for different σ .

PNN		RBF	
σ	Accuracy	σ	Accuracy
0.25	92.34	0.14	92.34
0.15	96.4	0.15	91.56
0.13	94.67	0.16	90.67
0.21	93.50	0.17	91.60
0.18	95.12	0.18	97.1
0.22	97.1	0.19	95.23
0.10	91.6	0.20	93.4
0.28	89.82	0.21	94.54

PNN network with $\sigma = 0.22$ and RBF network with $\sigma = 0.18$ have the most classification accuracy value. The result of fingerprint images' classification by means of neural networks with the percent of disapproval in each of them for 4 classes is illustrated in table 3.

Table 3: Result of classification with different networks.

Classifier	Classification accuracy for 4 class	Disapproval percent for 4 class
MLP	96.6	2.2
PNN	97.1	2.1
RBF	96.9	2.4

As you can see in table 4 the PNN network with 97.1% classification accuracy has the best performance among the other 4 networks. If the classification is done in 4 classes (plain loop and double loop whorl classes stand in the same class) this amount will increase to 97.1%. Table 4 illustrates the superior performance of our proposed approach related to other reports.

Table 4: A comparison of fingerprint classification algorithms with our algorithm

Method	Class	Accuracy
Jain and Minut	4	91.3
Mohamed and Nyongesa	5	92.4
Zhang et al.	5	84.0
Yao et al.	5	89.3
Yao et al.	5	89.3
Chang and Fan	5	94.8
Proposed Method	4	97.1

5. Conclusion

In this research a new method for feature extraction was proposed. Classifying extracted features by means of this method lead to better results in comparison with the related works. The characteristic vector produced in this method, not only contains valuable information about the concentration of ridges but also, has some information about ridges themselves. In addition characteristic vectors not only are resistant towards noise but also, they are insensitive to the input image transmission. It is interesting that all these advantages are achieved in a short time and with low costs. Required time for feature extraction from an image with a 2.4 GHZ processor in Matlab software environment is 0.14 second. The best classification accuracy for 4 classes is achieved by means of PNN network. This network had 95.5 accuracy and 2% disapproval. The best classification accuracy in 5 classes (97.1% with 2.1% disapproval) is achieved by means of PNN network. While Chang et al. [5] reported the classification accuracy in 5 classes as 94.8% (with 4.2% disapproval). In addition Shah et al. in [4] reported classification accuracy in 4 classes as 98% (with 4% disapproval). This accuracy value was achieved in a long period of time and with high computational costs. In table 4 a comparison between the performances of the proposed algorithm with the best reported results of related works is illustrated. In order to improve the performance of the proposed algorithm we can use hybrid classifiers to increase the accuracy of classification. For example, concomitant use of KNN and MLP networks for classification are recommended. Also we can increase the classification accuracy by detecting and disapproving those images which do not have general information about fingerprints.

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