Fingerprint Verification Based on Back Propagation Neural Network

Ala Balti*, Mounir Sayadi*, Farhat Fnaiech*,**

**SICISI Unit, High school of sciences and techniques of Tunis (ESSTT), 5 Av. Taha Hussein, 1008 Tunis, Tunisia , (e-mail: ala.balti.esstt@gmail.com, mounir.sayadi@esstt.rnu.tn)*
***Laboratory for Innovation Technologies (LTI-UPRES EA3899), Electrical Power Engineering Group (EESA), University of Picardie Jules Verne, 7, rue du Moulin Neuf, 80000 Amiens, France, (e-mail: fnaiech@ieee.org)*

Abstract: This paper is concerned with novel features for fingerprint classification based on the Euclidian distance between the center point and their nearest neighbor bifurcation minutiae's. The main advantage of the new method is the dimension reduction of the features vectors used to characterize fingerprint, compared with the classic characterization method based on the relative position of bifurcation minutiae points. In addition, this new method avoids the problem of geometric rotation and translation over the acquisition phase. Whatever, the degree of fingerprint rotation, the extraction features used to characterize fingerprint remains the same. The characterization efficiency of the proposed method is compared to the method based on the spatial coordinate of fingerprint minutiae's. The comparison is based on a characterization criterion, usually used to evaluate the class quantification and the features discriminating ability. After that, the classification accuracy of the proposed approach is evaluated with Back Propagation Neural Network (BPNN). Extensive experiments prove that the fingerprint classification based on a novel features and BPNN classifier gives better results in fingerprint classification than several other features and methods. Finally the results of the proposed method are evaluated on the FVC 2002 database.

Keywords: Back Propagation Neural Network, Fingerprint, Minutiae, Neural Network, Verification.

1. INTRODUCTION

Over the past years, many algorithms of fingerprint classification have been proposed in the literature, they used to extract distinguishable features and improving fingerprint recognition performance. (Panich, 2010; Balti *et al.*, 2012; Balti *et al.*, 2012 a, b) propose a new method of Fingerprint Identification. So, several approaches are based on singularities detection, center and delta points. (Zhang *et al.*, 2004), have used singularities with pseudo ridges to classify fingerprints. So, the classification approach based on singularity rules works very well if the singularities are accurately detected. But, they aren't sensitive to rotation and translation image fingerprints.

So far, several techniques have been proposed in the literature, based on minutia localizations, positions and orientations. So, the location and orientation of minutiae points is very important for fingerprint authentication. They are extracted from the thinned image which is obtained in the preprocessing step. After obtaining the feature vector, we found the matched fingerprint by comparing the matching score with a fixed threshold. The matching score is computed on comparing the minutiae points from two fingerprint images.

Furthermore, the features classification is a very tiring task and time consuming. To solve this problem, there are new techniques called intelligent classifiers based on the supervised neural network. (Santhanam *et al.*, 2010; Veluchamy *et al.*, 2012) have used the neural network approach in order to match two fingerprints taken from the same database.

Neural networks are now one of the most commonly used classifiers for fingerprint classification systems. Indeed, (Veluchamy *et al.*, 2012) have developed a neural network classification system and feature of Blood Cells. Since, several works use feed-forward neural network to classify feature vectors consisting of 64 wavelet coefficients. However, due to the limitations of the feature set, the results from this system are not very impressive. Furthermore, Mohamed and Nyongesa (Mohamed *et al.*, 2002) described the fuzzy-network classifier used to classify fingerprints based on singularity features. The features used include the number of core and delta points, the orientation of core points, the relative position of core and delta points and the global direction of the orientation field.

(Yusoff *et al.*, 2010) propose the verification techniques to digital evidence authentication. (Basha *et al.*, 2011) implement the multimodal biometric systems to overcome the limitations by using multiple pieces of evidence of the same identity. (Ponnarasi *et al.*, 2012) propose the use of minutiae's detection using Crossing Numbers (MDCN) and minutiae's detection using Midpoint Ridge Contour Method (MDMRCM). (Al-Omari *et al.*, 2009) use neural network to recognize isolated Arabic digits exist in different applications, (Petrisor *et al.*,. 2010) Analyze several approaches to microbial imagery enhancement, quantification, and classification.

Finally, Radu (Radu *et al.*, 2010) propose a fuzzy logic algorithm based on correlating a minutiae set and the regions between ridges for matching partial fingerprints. Boiangiu (Boiangiu *et al.*, 2013) describe a collection of algorithms for detecting text areas in document images using morphological operators.

In the rest of this paper I have employed the features based on the Euclidian distance between the center point and their nearest neighbor bifurcation minutiae points as input layer for the feed-forward back-propagation neural network, and I have compared the result with the relative position of minutiae points.

The remainder of this paper is organized as follows: section 2, 3 ,4 and 5 introduce, respectively, fingerprint images enhancement, locating reference point and minutiae's extraction and describes the proposed method of novel features vector for fingerprint characterization based on the center point and their nearest neighbor bifurcation minutiae's. Section 6 describes the materials and methods used in this experiment and presents the features discriminating ability and the neural network verification. Section 7 discusses our detailed experimental results and the criteria used to evaluate the class quantification and gives the performance of this proposed technique when applied to a range of fingerprint images. Finally, we conclude in Section 8.

2. FINGERPRINT IMAGES ENHANCEMENT

The fingerprint enhancement algorithm based on Gabor filer was first proposed by Hong (Hong *et al.*, 1998). Gabor filter performs a low pass filtering along the ridge orientation and a band pass filtering orthogonal to the ridge orientation. Because it's tuned to the two intrinsic properties of fingerprint, ridge orientation and ridge frequency. It can efficiently remove the undesired noise and preserve the true ridge and valley structures.

We have used the Hong's Gabor filter based enhancement algorithm. The Hong's algorithm mainly includes five steps:

Step 1: Normalization: an input fingerprint image is normalized so that it has a pre-specified mean and variance.

Step 2: Local orientation estimation: The orientation fingerprint is estimated from the normalized input fingerprint image.

Step 3: Local frequency estimation: The frequency fingerprint is computed from the normalized input fingerprint and the estimated orientation image.

Step 4: Region mask estimation: The region mask is obtained by classifying each block in the normalized input fingerprint image into a recoverable or a unrecoverable block.

Step 5: Filtering : a bank of Gabor filters which is tuned to local ridge orientation and ridge frequency is applied to the ridge and furrow pixels in the normalized input fingerprint image to obtain an enhanced fingerprint image.

In Hong's algorithm, the modulation transfer function of the Gabor filter is showed in following equation:

$$G(u, v : \phi, f) = \exp\left\{-\frac{1}{2}\left[\frac{u_\phi^2}{\delta_u{}^2} + \frac{v_\phi^2}{\delta_v{}^2}\right]\right\}\cos\left(2\pi f u_\phi\right) \quad (1)$$

$$u_\phi = u\cos\phi + v\sin\phi \quad (2)$$

$$v_\phi = -u\sin\phi + v\cos\phi \quad (3)$$

where ϕ is the orientation of the Gabor filter, f is the frequency of the cosine wave, u_ϕ and v_ϕ define the x and y axes of the filter coordinate, respectively. δ_u and δ_v are the standard deviations of the Gaussian envelope along the x and y axes, respectively. Figure1 shows the intensity map of a 2-D Gabor function used for fingerprint enhancement.

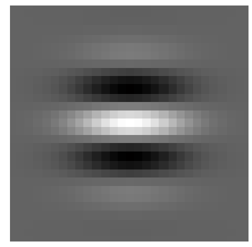


Fig. 1. Intensity map of a 2-D Gabor function used for fingerprint enhancement.

3. LOCATING REFERENCE POINT

After enhancing fingerprint image, we determine the position of the reference point from the enhanced image. In fingerprint image, the reference point of a fingerprint can be defined as the point of maximum curvature of the concave ridges in the fingerprint image, and it is the center of the region of interest (ROI). So, locating the reference point is an essential step that can influence the matching accuracy. However, we find that is insensitive to fingerprint rotation. Several methods can be used to locate the reference point (Maltoni *et al.*, 2009). In our algorithm, sometimes, we use the Poincar index for detection of the reference point, but the Poincar index analysis is a very classic method to locate the center point and the Poincar method can not detect the arch type fingerprint. Several approaches, (Chaorong *et al.*, 2012; Nilsson *et al.*, 2003) use complex filters to detect the reference point. In our work we use the complex filters to locate the reference point because each type of fingerprint, arch, whorl and loop, has different ridge flows.

Figure 2 shows the results of the reference point location of fingerprint image taken from FVC2002.

Fig. 2. Reference point location of fingerprint image taken from FVC2002.

4. MINUTIAE'S EXTRACTION

The most commonly employed method of minutiae extraction is the Crossing Number (CN) concept (Thai, 2003). This method uses the skeleton image and the minutia's are extracted by scanning the local neigh bourhood of each ridge pixel in the image using a 3×3 window. The ridge pixel can then be classified as a ridge ending, bifurcation or non-minutiae point. For example, a ridge pixel with a CN of one corresponds to a ridge ending minutiae, and a CN of three corresponds to a bifurcation minutiae. Ridge ending and bifurcation minutiae are shown in figure 3. We used the Minutiae extraction algorithm described in (Thai, 2003).

Figures 4 and 5 illustrate the results of extracting minutiae from a medium quality fingerprint image taken from FVC 2002. From the skeleton image, it can be deduced that all ridge pixels corresponding to a CN of one and three have been detected successfully.

The flowchart of the fingerprint enhancement algorithm, locating reference point and proposed fingerprint matching approach is shown in Figure 6.

5. PROPOSED FINGERPRINT CHARACTERIZATION BASED ON CENTER POINT AND THEIR NEAREST NEIGHBOR BIFURCATION POINTS

The recognition system is to extract some features vector (minutiae or otherwise) in the form of coded information and compare there with another features vector registries in the database.

In general, there are in literature two categories of fingerprint recognition algorithms: the first are conventional algorithms that are based on the relative position of minutiae, the second includes the algorithms to extract other features of the fingerprint such as the local orientation field or the frequency of the local texture in the centre of the image.

Our method is part of the first categories. After filtering the image, the binarisation and thinning of fingerprint is performed successively, then we extract the position of minutiae and the center point. The goal is to quantify the characteristics of similarity between two templates. To do this, it is necessary to define a vector characterizing a fingerprint identity.

In our method of fingerprint recognition, we extract the feature vector for each fingerprint. It contains the position of center point and position of bifurcation minutiae points. So, for each deduced and validated center point and minutiae points they extract two characteristics, they are the spatial coordinates with x and y pixels and the orientation field for each extracted points. After validation of the minutiae's, we have a feature vector, containing N_p minutiae's, where M_B: bifurcation minutiae. The feature vector S_p is the least useful information contained in the image and necessary for fingerprint identification:

$$S_p = \{M_B\} \tag{4}$$

$$M_B = \{X_i , Y_i , \Phi_i\} \quad i \in [1...N_B] \tag{5}$$

$$N_P = \{N_B\} \tag{6}$$

We proposed an improved features vector for fingerprint characterization method, it based on the Euclidian distance between the center point and their validated neighbor bifurcation minutiae points.

The main advantage of the new method is the reduced number of features vectors used to characterize finger print, compared with the classic characterization method based on the spatial coordinates of bifurcation minutiae's. In addition this new method avoids the problem of geometric rotation and translation over the acquisition phase of image fingerprints.

After extraction of the position of the center point and minutiae points, we compute the Euclidian distance between them, there is the improved features vector S_p. After that, we will save it in the database. Then we compare the desired vector with the S_q saved vector S_p. These two features vectors will never be exactly the same.

The fingerprint identification is to compute the similarity rate between two signatures. Then, this rate will be compared with a threshold T set in advance according to the selected application.

Steps of our improved features for fingerprint identification algorithm are shown in figure 6. Enrollment stage:

Step 1: Detect center point and save it in the database, there is the first fingerprint characterization.
Step 2: Detect bifurcation minutiae and save it in the database, there is the second fingerprint characterization.
Step 3: For i = 1 until N_p

Compute the Euclidian distance between the center point and minutiae points as follow:

$$ED(i) = \mathrm{dist}(M_C , M_{i,j}) \tag{7}$$

where, M_c and $M_{i,j}$ are the spatial coordinates for the center point and the bifurcation minutiae points, respectively:

Step 4: Sort the Euclidian distance vector between the center point and minutiae in ascending order.
Step 5: Save the Euclidean distance vector in the data base. It's the improved features.
Step 6: Training of the supervised neural network and make decision of classification.

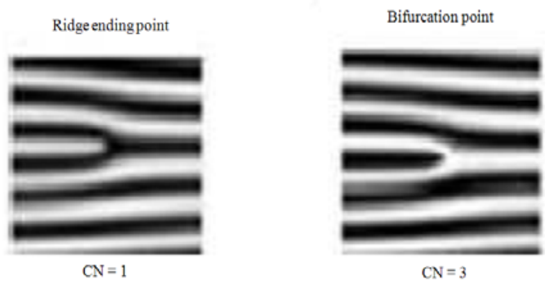
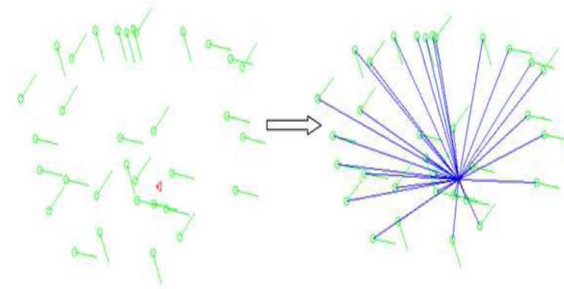


Fig. 3. Examples of a ridge ending and bifurcation pixel.

(a) (b)

Fig. 4. Fingerprint image with extracted minutiae points, Red: Center point, Blue: Bifurcation minutiae points (a) Physical Fingerprint image (b) Automatic detection of minutiae.



(a) (b)

Fig. 5. Extracted bifurcation minutiae points (circle green) and center point (red triangle).

6. MATERIALS AND METHODS

The performance evaluation protocol used in FVC2002 is adopted in this experiments (Maio *et al.*, 2002). So, we firstly introduce several performances indicator of fingerprint verification such as: False acceptance rate (FAR), which is the rate that an imposter fingerprint is incorrectly accepted as a genuine claims, equivalent to the probability that an unauthorized person is incorrectly accepted as authorized

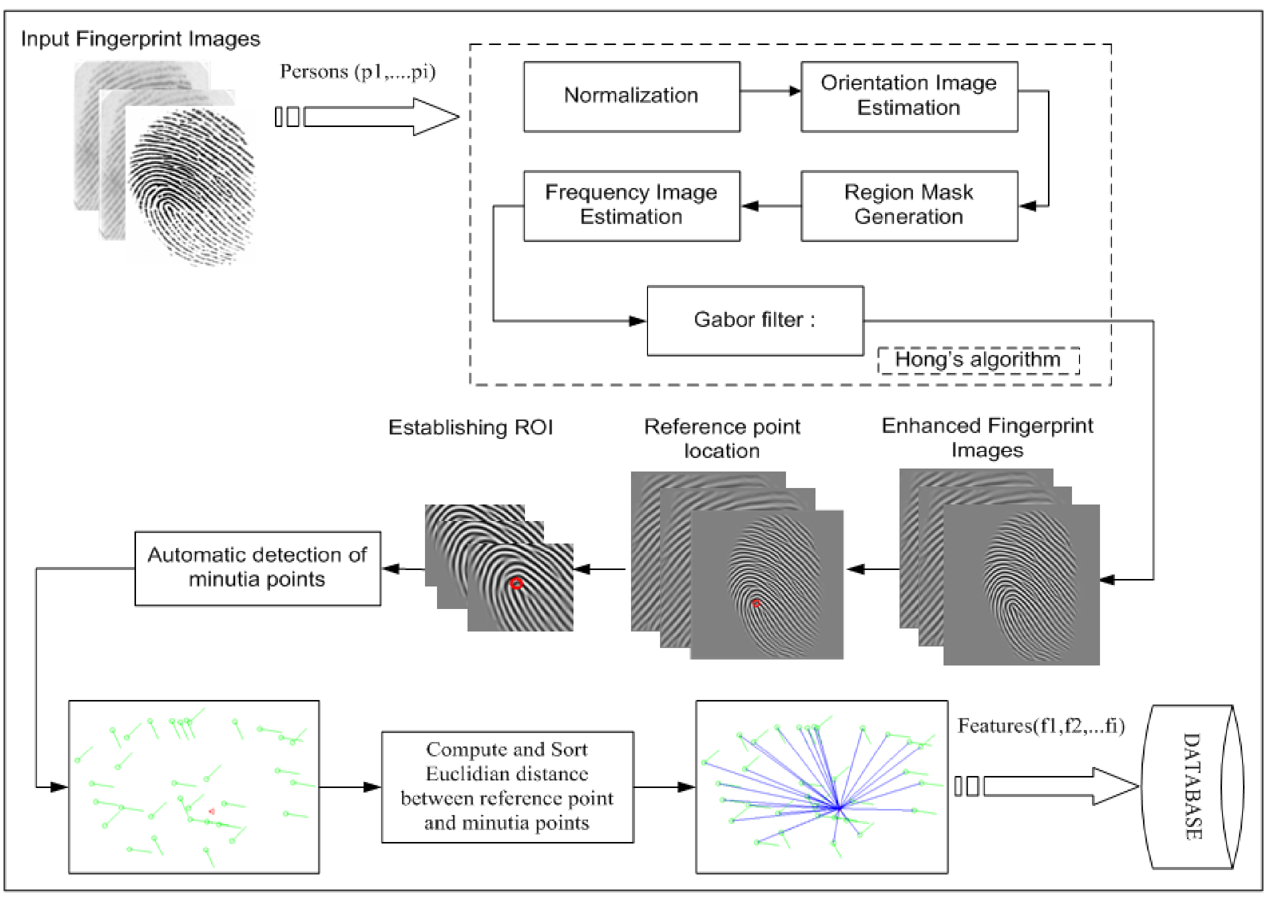


Fig. 6. Flowchart of fingerprint enhancement algorithm, locating reference point and proposed fingerprint matching approach.

person, False Reject Rate (FRR), .which is the rate that a genuine fingerprint is incorrectly rejected as an imposter claims, equivalent to the probability that the system does not detect an authorized person. Equal Error Rate (EER): it is the rate at which both accept and reject rates are identical. The EER is used as a performance indicator. Genuine acceptance rate (GAR), which is the rate that a genuine fingerprint is correctly accepted as genuine. The GAR, FAR and FRR are defined as follows:

$$GAR = \frac{Number\ of\ accepted\ genuine\ finger}{Total\ number\ of\ genuine\ finger} \times 100 \tag{8}$$

$$FAR = \frac{Number\ of\ accepted\ imposter\ finger}{Total\ number\ of\ imposter\ finger} \times 100 \tag{9}$$

$$FRR = \frac{Number\ of\ rejected\ genuine\ finger}{Total\ number\ of\ genuine\ finger} \times 100 \tag{10}$$

The Equal Error Rate (EER), False Reject Rate (FRR) and False Accept Rate (FAR) are computed on the four databases and the accepted fingerprint match (genuine) and rejected fingerprint match (impostor) were performed. For genuine fingerprint match, each test fingerprint of each person was compared with the template fingerprint of the same person. For impostor fingerprint match, the test fingerprint of each person was compared with the template fingerprint of other persons.

The verification performances of our proposed method with two matching methods over the four databases of FVC2002 were shown in the following.

The fingerprint image database used in this experiment is the FVC2002 fingerprint database (Maio *et al.*, 2002), which contains four distinct databases: DB1_a, DB2_a, DB3_a and DB4_a in 256 gray scale levels, each database consists of 800 fingerprint images (100 persons, 8 fingerprints per person). The fair and distinct fingerprint image databases are created with different scanners and time as shown in the figure 7.

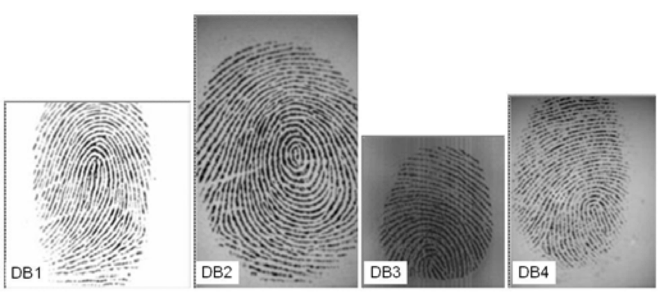


Fig. 7. Sample images from the four databases of FVC2002 (Maio et al. 2002; FVC 2002).

All tests and experiments are carried out by using MATLAB as computing environment and programming language.

7. RESULTS AND DISCUSSION

7.1 Experiment 1: Study of the Characterization Degree of the Fingerprint Features

Consider a set of 40 different gray of 374×388 pixels, extracted from the base DB1.a. In order to check whether the use of the Euclidean distance between the center point and their nearest neighbor bifurcation minutiae improves the fingerprint characterization compared with the spatial coordinates position and orientation of the extracted minutiae, we propose to evaluate the feature vectors with the characterization degree "CD" of each fingerprint feature vector extracted with the proposed method and the minutiae spatial coordinates position. For comparison reason of the experiment the characterization degree is detailed in the following.

Table 1. Characterization degrees of the studied fingerprints characterization methods (Statistical feature method, Co-occurrence feature method).

	"Characterization Degree" CD	
	Statistical method	Co-occurrence method
Minimum distance features between singularities (proposed method)	2.1056	0.9922
Minutiae spatial coordinates features	1.8053	0.9609

For an in-depth study of the characterization capability of the proposed features, we compute a "characterization degree" CD based on the ratio between the "inter variance" and the "intra-variance" of each feature finger print (Sayadi et al. 2010). All the 40 randomly chosen fingerprint from the

FVC2002 are used. Note: $\underline{x}_{k,n}$ the nth estimated feature vector for the kth fingerprint (1≤k≤40, 1≤n≤25). The mean of the kth fingerprint feature vector class is noted.

$$\underline{m}_k = \frac{1}{100}\sum_{n=1}^{100}\underline{x}_{k,n} \tag{11}$$

And the mean of all the features vectors class is.

$$\underline{m}_c = \frac{1}{25}\sum_{k=1}^{25}\underline{m}_k \tag{12}$$

The mean of the within class (intra-class) dispersion matrices is given by the matrix.

$$\underline{S}_{intra} = \frac{1}{2500}\sum_{k=1}^{25}\sum_{n=1}^{100}\left(\underline{x}_{k,n} - \underline{m}_k\right)\left(\underline{x}_{k,n} - \underline{m}_k\right)^t \tag{13}$$

Complementary to this is the mean of the between-class (inter-class) dispersion matrices which describes the scattering of the class sample means. It is calculated by the matrix

$$\underline{S}_{inter} = \frac{1}{25}\sum_{k=1}^{25}\left(\underline{m}_k - \underline{m}_c\right)\left(\underline{m}_k - \underline{m}_c\right)^t \quad (14)$$

So, the characterization Degree" CD is given by (Sayadi and Fnaiech, 2010).

$$CD = trace\left(S_{intra}^{-1}.S_{inter}\right) \quad (15)$$

This method proposes to extract a feature vector from each $\underline{x}_{k,n}$ fingerprint image with two methods: statistical method and co-occurrence method, in order to evaluate the characterization degree.

In the statistical method, the features vector contains the mean, the variance and respectively the third, the forth, the, the fifth and the sixth order moments.

In the co-occurrence method, the features vector contains the contrast, the correlation, the energy and the homogeneity.

The greater characterization degree for these two extracted features methods is the more robust classification process. The comparison of the ability of the studied features is presented through Table 2.

We notice that the characterization degree provided by center point and their nearest neighbor minutiae features is greater (2,1056 and 0,9922) than the characterization degrees provided by the Minutiae spatial coordinates features (1,8053 and 0,9609). The main advantage of the new method based on the center point and their nearest neighbor bifurcation minutiae is the invariant and reduced features vector for fingerprint characterization.

7.2 Experiment 2: Study of the neural network verification

The use of neural networks to fingerprint classification is very important, many research (Veluchamy *et al.*, 2012; Santhanam *et al.*, 2010) have continued until now to apply the supervised neural network for fingerprint classification. Figure 8 shows a schematic of the back propagation neural network classifier used in this study.

The optimal conditions for the classification were found to be a single hidden layer composed of 70 neurons and 17 neurons for the input layer (17 features as input), they having symmetric sigmoid (hyperbolic tangent) activation functions, and 1 output neurons corresponding to the number of image fingerprint in the database having linear activation functions. So the architecture of our feed-forward back propagation network is (17,70,1). In which the outputs are interpretable as probabilities of identification between fingerprint. Using linear activation functions in the output layer provides a measure of certainty, while classification accuracy is improved.

I have employed the features based on the Euclidian distance between the center point and their nearest neighbor bifurcation minutiae points as input layer for the feed-forward back propagation network, and I have compared the result with the relative position of minutia points.

The validation and test error (generalization) are very encouraging, it can be seen that the generalization capability of the neural network is satisfactory.

A supervised MLP neural network was employed for classification of fingerprint images. They tend to generalize better classification if all features are extracted far away (low redundancy of the elements of feature vector). Moreover, they give better performance with rapid speed convergence to the optimal solution.

Finally, the result of neural network training for classification of fingerprint images using invariant and reduced features based on the Euclidian distance between center point and their nearest neighbor minutiae features is better because they reduce the size of the vector classification, keeping the same classification performance and overcome the problems of geometric rotation. The comparison of the abilities of the studied features is presented through table 2.

Table 2. Result and comparison of the neural network classification.

	Minutiae spatial coordinates features	Minimum distance features between singularities (proposed method)
Input Layer	34	17
Hidden Layer	70	70
Output Layer	1	1
Iteration number (Epochs)	43	533
training errors	7.85×10^{-28}	3.72×10^{-26}
training temps	6 min and 5 sec	8 min and 3 sec

In the experiments of BPNN matching, the training data and testing data were normalized by dividing the features vector of each fingerprint into difference between max and min before training and testing neural network. Experimentally, the optimal number of hidden layers was determined to 70. The mean square error was $10e^{-20}$ and epoch was 533.

From the table 3, we can find that the average EER (%) values of Back Propagation Neural Network (BPNN) matching over four databases with our proposed method is 5.15% , on the other side, the average EER (%) of matching with position of fingerprint minutia's is 6.56%.

For a comparison study, the verification performance of our proposed method give an Equal Error Rate (EER) lower than method of position minutiae's. So, comparing with other famous methods, our proposed method performs better of accuracy. So, the experimental results show that the proposed method has a higher matching accuracy.

8. CONCLUSIONS

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

In this paper, we have proposed an improved feature for fingerprint identification. It is based on the Euclidian distance between the center point and their nearest neighbor bifurcation minutiae points. The performance of the identification fingerprint process was numerically assessed using the accuracy of our verification system, for a given dataset, fingerprint matching results from the proposed method are validated and the similarity score for the test data available is evaluated.

The evaluation of our method in comparison with other verification systems is very encouraging and it has proved its efficiency for identification of fingerprints. Then, we have used the supervised neural network classification, because the MLP are now one of the most commonly used classifiers for fingerprint classification systems. The validation and test error are very encouraging, it can be seen that the generalization capability of the neural network is satisfactory.

The main advantage of the new method is the dimension reduction of the features vectors used to characterize fingerprint, compared with the classic characterization method based on the relative position, furthermore it overcomes the problem of geometric rotation and translation over the acquisition phase of image fingerprints. We evaluated the performance of image and feature on the FVC 2002 dataset.

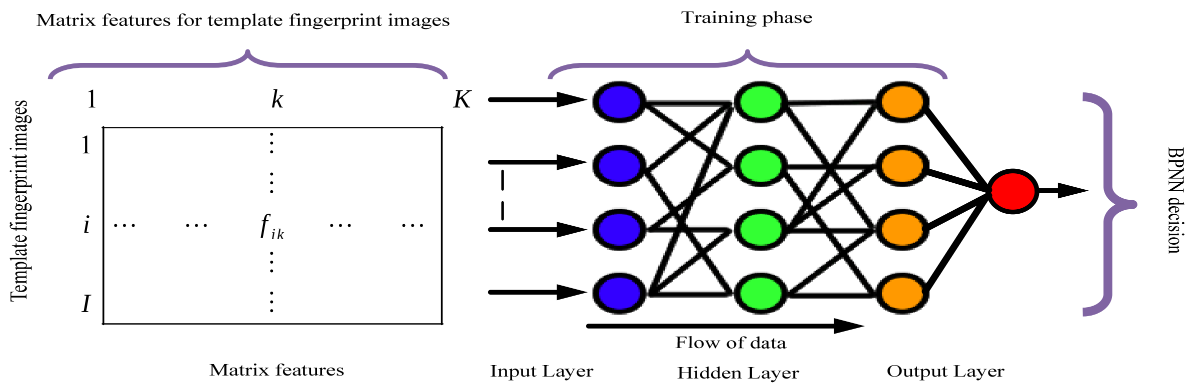


Fig. 8. Schematic of the Back Propagation Neural Network (BPNN) classifier architecture used for pattern recognition.

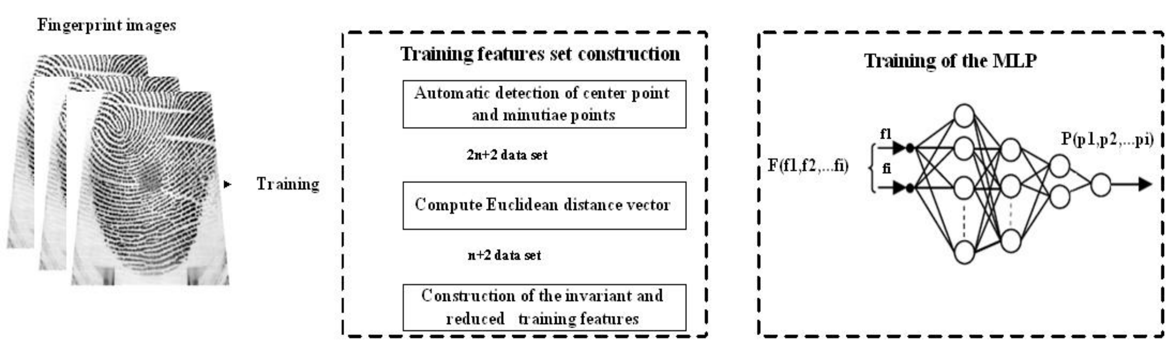


Fig. 9. Training phase of the MLP neural network classifier using invariant and reduced features.

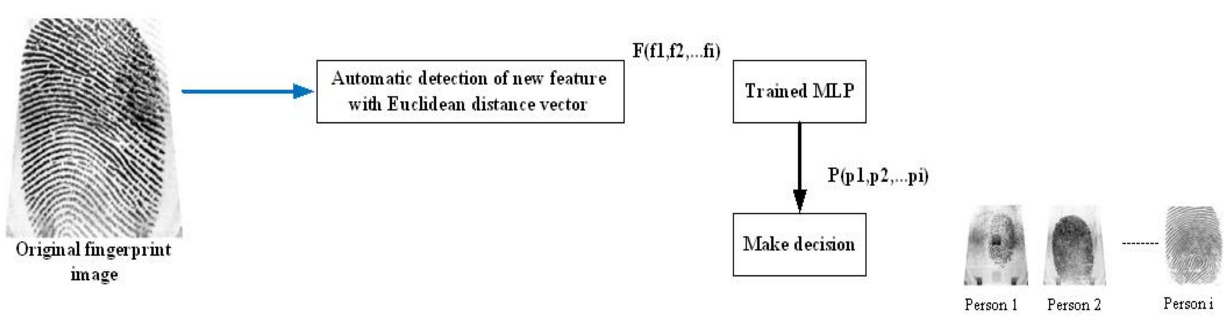


Fig. 10. Processing phase for fingerprint classification with trained MLP.

Table 3. Illustrates of the matching performances of the proposed method with the Supervised Back Propagation Neural Network (BPNN)over the four databases, using the comparison of the Equal Error Rate EER(%).

Equal Error Rate (EER)					
Database	DB1_a	DB2_a	DB3_a	DB4_a	Average
Matching with position of fingerprint minutiae's	5.93%	7.26%	6.64%	6.41%	6.56%
Matching with our proposed method	4.60%	5.32%	4.86%	5.82%	5.15%

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