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Proposal Fingerprint Recognition Regimes Development Based on Minutiae Matching

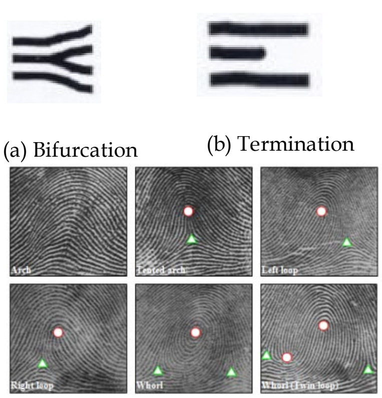
Hany Hashem Ahmed, Hamdy M. Kelash, Maha S. Tolba, Mohammed Badawy.
Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University, Egypt.

Abstract— Fingerprint recognition is one of the oldest and most popular biometric technology and it is used in criminal investigations, civilian, commercial applications, and so on. Fingerprint matching is the process used to determine whether the two sets of fingerprints details come from the same finger or not. This work focuses on feature extraction and minutiae matching stage. There are many matching techniques used for fingerprint recognition systems such as minutiae based matching, pattern based matching, Correlation based matching, and image based matching. Two fingerprint recognition regimes have been developed based on minutiae matching, the first one is: Artificial Neural Network based on Minutiae Distance Vector (ANN-MDV), while the other one is: Artificial Neural Network based on Principle Component Analysis (ANN-PCA). It is observed that the recognition rate is increased and return better result. A comparative study between the 2-developed system is done based on average recognition time (ART), and the accuracy of the recognition system. The experimental results are done on FVC2002 database. These results show that the accuracy of ANN-MDV system is approximately equal to 91%, and the accuracy of ANN-PCA system is approximately equal to 98%. Therefore ANN-PCA is the best recognition system accuracy. Also the experimental results show that ART for ANN-MDV (equal to 0.251) is slightly better than ANN-PCA (equal to 0.275).

Index Terms— Fingerprint Recognition, image enhancement, FDCT, Minutiae Distance Vector, ANN, BPN, PCA, ART.

1 Introduction

A fingerprint consists of a pattern of ridges (lines across fingerprints) and valleys (spaces between ridges) in a finger. The pattern of the ridges and valleys is unique, permanent for each individual, and remains unchanged over a lifetime. Minutiae (fingerprint features) are formed from the local discontinuities in ridge flow pattern. These minutiae have the required features that are used in fingerprint recognition system. There are many types of minutiae like Bifurcation, Termination, Lake, Spur, Crossover, dot, bridge, trifurcation, island, and singular points (core & delta). The considered types of extracted features used in this paper for fingerprint recognition are ridge bifurcation point, ridge termination point, core point, and delta point as seen in Fig. 1 [1, 2].



(a) Bifurcation (b) Termination

(c) Core & Delta points

Fig. 1 Types of minutiae

The technique used here for fingerprint recognition is based on minutiae matching. The fingerprint recognition system is a comparison between the input fingerprint image and the template fingerprint image stored previously in a database. The main purpose of this work is to develop a new technique for fingerprint recognition system that return an excellent results to query the input fingerprint image from the database in an acceptable response time. There are a large number of techniques that are being used for fingerprint recognition systems; one of them is artificial neural network (ANN). ANN is an efficient method for prediction and recognition. There are many types of network such as Perceptron , feed forward back propagation network, radial basis network, Hopfield recurrent network, pattern recognition network, etc.., in this paper feed forward back propagation network has been used for the developed system. In this paper for the 2-proposed systems, back propagation network is the best network in training and return relevant results. Two fingerprint recognition systems have been proposed and developed based on ANN, the first one system is ANN based on minutiae distance vector (ANN-MDV), and the second is ANN based on Principle component analysis (ANN-PCA). The rest of this paper is organized as follow: Section 2 discusses the principle of ANN, advantages of ANN, MDV description and explains the work of PCA. Section 3 shows the block diagrams of the 2-developed systems and discusses the main stages of each one. Section 4 shows the experimental results and examines the recognition systems. Section 5 presents a comparative analysis between the 2-developed recognition regimes, and introduces a comparison tables. The last section gives a brief summary, conclusion, and represents short notes for future work.

2 Related Work

This section presents a brief description about neural network, principle component analysis, and minutiae distance vector.

2.1 Minutiae Distance Vector (MDV)

Minutiae Distances (MDs) are the distances between the reference point (core point) and all minutiae points (bifurcation, termination, and delta points). Minutiae Distance Vector (MDV) can be calculated by sorting these estimated distances (MDs) in ascending form and put it in one vector.

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2.2 Principle Component Analysis (PCA)

Due to great difficulties in determining similarities and differences between data arising from large patterns of data, therefore we use PCA to solve this problem. PCA is an efficient and a powerful tool for analyzing data patterns. Another important feature of PCA is the ability to compress data by reducing the number of dimensions without losing much information. Finally PCA could be defined as a statistical procedure (variance, covariance, mean, eigenvector….etc.) used to convert patterns of data with related variables into a set of values of non-related variables called principal components (PC), these PCs are always less than or equal to the original related variables [3, 4].

2.3 Artificial Neural Network (ANN)

Definition: ANN is an information processing system that has certain performance characteristics similar to biological neural network. Description: neural network consists of large number of simple processing units called neurons or nodes. Each node is connected to the other nodes by direct communication links. Each link has an associated weight. The weight contains information used by the network to solve the problem [5, 6]. ANN can be used to store and query data or pattern, classify pattern and find solution to constrained optimization problems. Fig. 2 shows a simple neuron [7].

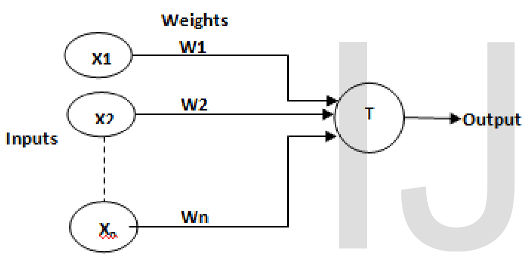


Fig. 2 Simple neuron or node.

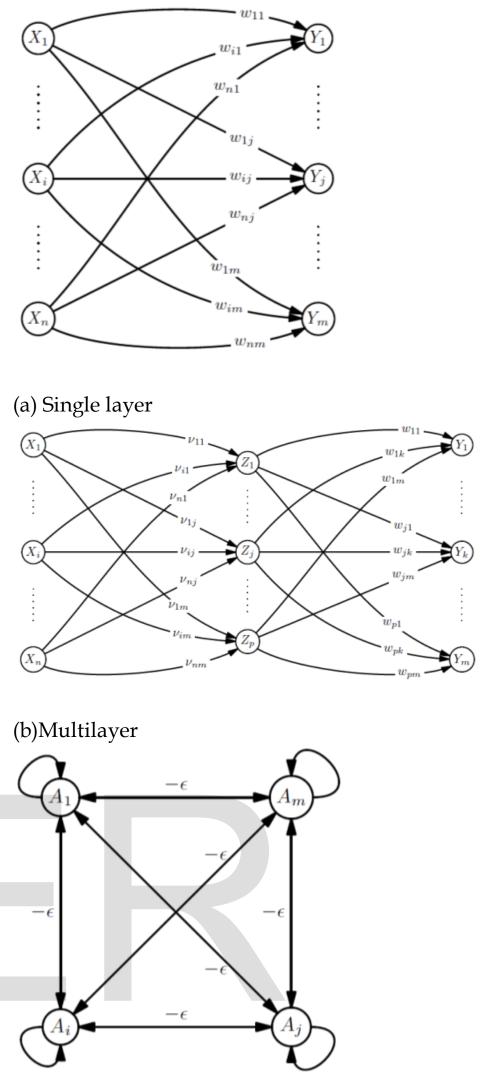
The function of simple neuron can be described by (1).

$$output = \begin{cases} 1 & if\ \sum_{i=1}^{n} wi \cdot xi \geq T \\ 0 & if\ \sum_{i=1}^{n} wi \cdot xi < T \end{cases} \quad (1)$$

Where T is threshold, X_i is the input to neuron, W_i is the weight, and n is the number of inputs.

The neural network is characterized by:

1- Architecture: is a pattern of connections among the neurons (arrangement of neurons into layer) [7]. As shown in Fig. 3 there are three architecture types as follow:
   a. Single layer feed forward network: has one layer of connection weights
   b. Multilayer feed forward network: is a network with one or more layer (called hidden layer) between the input units and the output units.
   c. Recurrent network: there are closed loop signal paths from a unit back to itself.



(a) Single layer

(b)Multilayer

(c) Recurrent

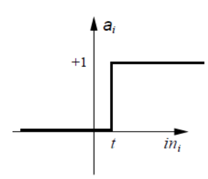
Fig. 3 Neural network architectures

2- Training or learning types: are methods to estimate the weights on the connections. Learning types:
   a. Supervised learning: each input vector of the network has an associated target output vector. Every learning cycle the error (difference between the actual and desired output) is used to adjust the weights.
   b. Unsupervised learning: the input vectors are provided to the network, but with no associated target vectors. The weights are adjusted so that the similar input vectors are assigned to the same output.

3- Activation functions: determine how the output of the neuron will be calculated [7]. Some of the activation functions are seen in Fig. 4.
   a. Binary step function (with threshold t).
   b. Bipolar binary function.
   c. Sigmoid function.

$$f(x) = \begin{cases} 1 & if \quad x \geq t \\ 0 & if \quad x < t \end{cases} \quad (2)$$

(a) Binary step function with threshold *t*.



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$$f(in) = \begin{cases} 1 & if \quad in \geq 0 \\ -1 & if \quad in < 0 \end{cases} \qquad (3)$$

(b) Bipolar binary function.

$$f(in) \triangleq \frac{1}{1 + \exp(-in)} \qquad (4)$$

(c) Sigmoid function.

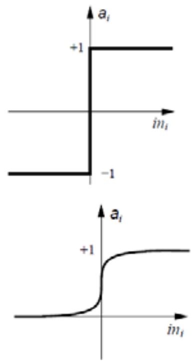

Fig. 4 Activation functions.

3 Proposed System

Tow systems are developed as follow:
First system: Fingerprint recognition system using ANN based on MDV.
Second system: Fingerprint recognition system using ANN based on PCA.

3.1 Fingerprint recognition system using ANN based on MDV

The design of the first developed system is shown in Fig. 5.

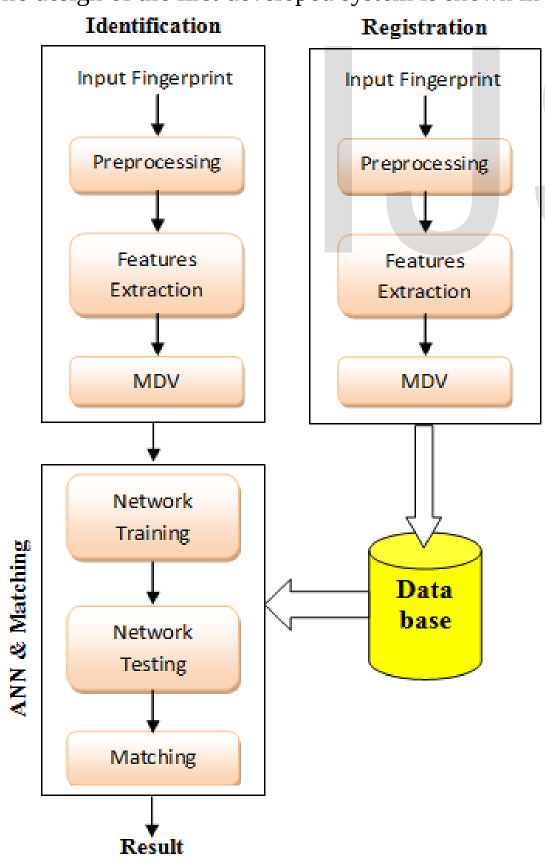

Fig. 5 Fingerprint recognition ANN-MDV

The stages of the algorithm are fingerprint image acquisition, preprocessing, features extraction, minutiae distance vector, training the network, testing the network, matching the input fingerprint with stored fingerprint images in data base, finally estimate the result.

1) Preprocessing stage

The algorithm of preprocessing stage is shown in Fig. 6.

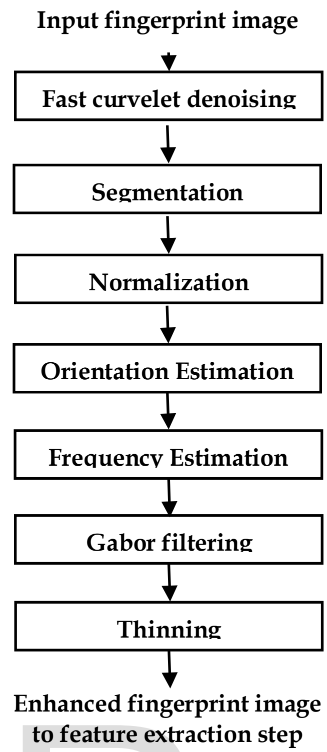

Fig. 6 Preprocessing stage

Practically the input fingerprint image may be noisy and corrupted due to environmental factors or body condition of the user. So that it is very important to do some preprocessing steps on the input fingerprint image in order to improve the clarity of ridge structure and increase the performance of minutiae extraction algorithm. Therefore the main purpose of preprocessing stage is to enhance and preparing the input fingerprint image for next stage. The steps of preprocessing stage are:

Step 1. Fast curvelet denoising: In this step fast curvelet is used to eliminate different kinds of noise such as random noise, salt noise, speckle noise and Gaussian noise form fingerprint images. The algorithm of fingerprint image denoising done by:

1- Compute all thresholds of curvelet which will be applied to image curvelet coefficient.
2- Normalize the curvelet coefficient.
3- Perform warping Fast Discrete Curvelet Transform (FDCT) to the noisy image and transfer it from spatial domain to curvelet domain.
4- Apply the computed threshold in step1 to the curvelet coefficients.
5- Apply inverse fast discrete curvelet transform to the result in order to transfer the image from curvelet domain to spatial domain (original state) [8, 9].

Step 2. Segmentation: Is the process of separating the foreground regions (contain fingerprint information which is called the Region of Interest ROI) from the background regions (noisy area) in the fingerprint image [10].

Step 3. Normalization: The main purpose of normalization is to reduce the differences in the grey level values and enhance the contrast of the fingerprint image, so that the ridges and valleys of the normalized image can be easily distinguished [1].

Step 4. Orientation estimation: In this step the dominant direction of the ridges and valleys in the fingerprint image is estimated [11].

Step 5. Frequency estimation: The local ridge frequency is defined as the frequency of the ridge and valley structures in a local neighborhood along a direction orthogonal to the local ridge orientation. The ridge frequency is also varying slowly and hence it is computed only once for each non-overlapping block of the image [12].

Step 6. Gabor filter: The purpose of this step is to remove noise and preserve the ridge and valley structures [13].

Step 7. Thinning (skeletonization): After the thinning process is applied on the fingerprint image, the ridge width becomes one pixel size (skeleton fingerprint image). The ridge thinning process make the features extraction and marking minutiae points are very easy [14].

2) Feature extraction stage

Fingerprint image contains a lot of minutiae such as ridge termination, ridge bifurcation, short ridge, island, crossing point, delta point, and core point. But the interested and most important features considered in this paper are ridge termination, ridge bifurcation, and singular points as shown in Fig. 7. Core Point is the topmost point on the innermost upwardly curving ridgeline (approximately center of the fingerprint). Core point is considered as reference point for reading and classifying the fingerprint image. Delta point is defined as the point on the first bifurcation, meeting of two ridges, fragmentary ridge, abrupt ending ridge dot, or any point on a ridge at or in front of and nearest to the center of the divergence of the type lines. Poincare index algorithm is used to extract the singular points core and delta.

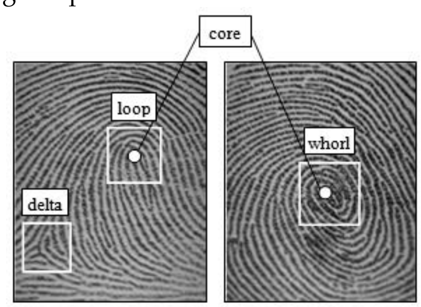

Fig. 7 A core and a delta singularity in a right loop fingerprint [1].

The algorithm used for extracting features from fingerprint image is Crossing Number (CN) which consider (3x3) pixel window as shown in Fig. 8.

P4	P3	P2
P5	P	P1
P6	P7	P8

Fig. 8 A 3 x3 window is placed on a binary image, pixel P with its 8 neighboring points (P1, P2……P8).

If the central pixel (P) is 1 and has only 1 one-value neighbour, then the central pixel is a ridge termination point. Also if the central pixel (P) equal to 1 and has exactly 3 one-value neighbors, then the central pixel is a ridge bifurcation point. The CN value can be estimated by (5).

$$CN = 0.5 \sum_{i=1}^{8} |P_i - P_{i+1}| \quad , \qquad P_9 = P_1 \qquad (5)$$

Where P_i is the pixel value in the neighborhood of P. The pixels can be classified according to the value of CN as shown in table 1 [10, 15].

TABLE1 MINUTIAE CLASSIFICATION

CN	Pixel classification
0	Isolated point
1	Termination point
2	Connective point
3	Bifurcation point
4	Crossing point

Remove false minutiae: removing false minutiae is very important step for the accuracy of fingerprint recognition system. The algorithm of removing false minutiae as follows:

1. First we calculate the average distance "D" between 2-parallel neighboring ridges and suppose D as threshold for false minutiae.
2. If the distance between ending point and bifurcation point is less than D and the two minutiae are in the same ridge, then remove both of them.
3. If the distance between two bifurcations is less than D and they are in the same ridge, remove the two bifurcations.
4. If the distance between 2-terminations is less than D, remove the two terminations.
5. If 2-termination points are within a distance D and their directions are coincident with a small angle variation, then the 2-termination points are considered as false minutia and are removed.

Direction and angle of correct minutiae: As discussed before the important minutiae points are ridge ending "CN = 1" and ridge bifurcation "CN = 3", therefore the direction and angle of these minutiae are very important. The 8 directions (N, S, W, E, NE, NW, SE, and SW) can be determined by the following pseudo code:

```
% for ridge ending point
If CN = 1 then
  If P1 = 1 then direction = W
  If P3 = 1 then direction = S
  If P7 = 1 then direction = N
  If P5 = 1 then direction = E
  If P4 = 1 then direction = SE
  If P2 = 1 then direction = SW
  If P6 = 1 then direction = NE
  If P8 = 1 then direction = NW
End if
% for ridge bifurcation point
If CN = 3 then
  If P1 and P3 and P7 = 1 then direction = W
  If P1 and P3 and P5 = 1 then direction = S
  If P1 and P7 and P5 = 1 then direction = N
  If P3 and P5 and P7 = 1 then direction = E
  If P4 and P3 and P5 = 1 then direction = SE
  If P3 and P2 and P1 = 1 then direction = SW
  If P3 and P5 and P6 = 1 then direction = NE
  If P4 and P8 and P5 = 1 then direction = NW
```

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End if [16].

3) Minutiae Distance Vector (MDV) stage

MDV is the input vector to the neural network. This vector can be obtained and formed by calculating the distance between each minutiae coordinates & the reference point (core point), and then these distances are sorted in ascending form. After MDVs are formed for all fingerprints images, these vectors will be saved and stored in a database and will be input to the neural network.

4) ANN Training stage

Practically, the best artificial neural network type for fingerprint recognition system is feed forward back propagation network. Structure of feed forward back propagation network is shown in Fig. 9.

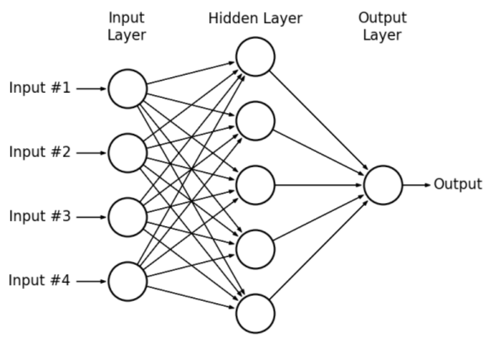

Fig. 9 Structure of back propagation neural network [7]

Once the network structure has been created, the training phase is ready to begin. The input data (MDVs) are divided into training set 70%, testing set 15%, and validation set 15%. The supervised training technique has been chosen to train feed forward back propagation network. Neural network units (neurons) are trained with Scaled conjugate gradient back propagation algorithm called (trainscg). Performance function of the developed network is Mean squared error with regularization performance function (msereg). The activation transfer function used in the network is hyperbolic tangent sigmoid transfer function (tansig). The training algorithm as follow [7]:

1. Select a training pair from the training set (apply the first input vector to the network input).
2. Calculate the output of the network.
3. Calculate the error between the network output and the desired output (the target vector from the training pair)
4. Adjust the weights of the network in a way that minimizes the error.
5. Repeat the steps 1 through 4 for each input vector in the training set until the error for the entire set is acceptably low [17].

5) ANN Testing stage

After the training stage has been completed, the testing and validation stage are applied on different samples to check the performance of the network [17].

6) Matching stage

It is the final stage in fingerprint recognition system which is used to identify the input fingerprint image. The algorithm of matching process is to assign each fingerprint image (represented by MDV vector), to one class named by Pi (where, i=101, 201...), for example finger print of the first person is corresponding to class P101, the second person is corresponding to class P201, and so on. Then these data will be stored in data base for matching process. Now the network is ready to identify the fingerprint image. When the input fingerprint image enters to the system, minutiae are transferred to a vector, and then the network simulates this vector and gives the result.

3.2 Fingerprint recognition system using ANN based on PCA

The algorithm of this system is shown in Fig. 10. There is only one big difference between the 2-developed systems in which PCA is used instead of MDV in stage 3.

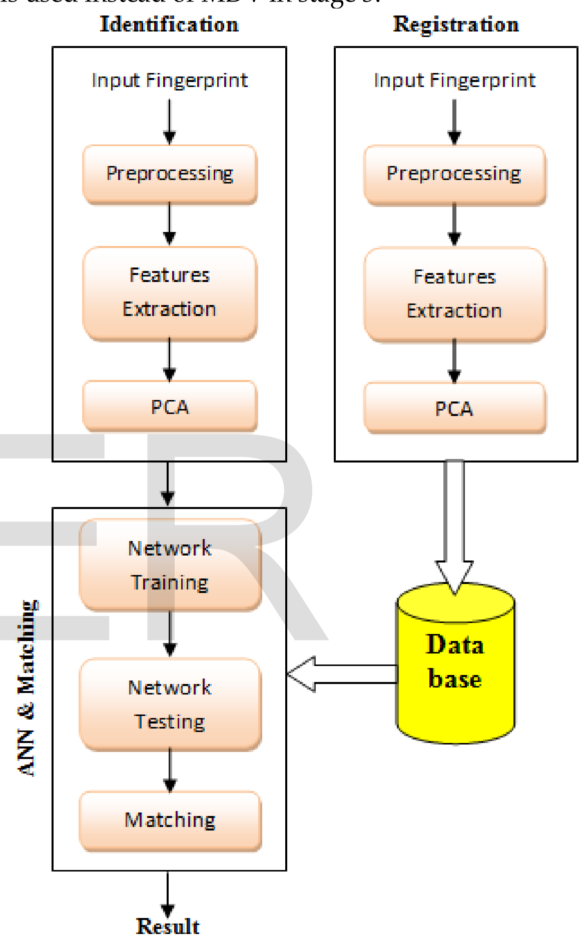

Fig. 10 Fingerprint Recognition ANN-PCA

Steps:

1. Preprocessing: As mentioned before.
2. Feature extraction: As mentioned before.
3. Principal Component Analysis (PCA): After the minutiae have been extracted from fingerprint image, the minutiae matrix is created. PCA is used to reduce and compress the matrix data. Matrix data can be converted using PCA to principal component coefficients, principal component scores, or eigenvalues of the covariance matrix. The conversion of matrix data to principal component coefficients is developed and used here in fingerprint recognition system. Then these coefficients are reshaped to vectors form. The vectors of principal component coefficients are stored into the database and then they are treated as input of neural network.

4. Ann training: As mentioned before.
5. Ann testing: As mentioned before.
6. Matching: As mentioned before.

4 Experimental Results

In the obtained experimental results we use sample of 100 fingerprint images with 500dpi resolution derived from FVC2002 database (http://bias.csr.unibo.it/fvc2002/ download.asp). FVC2002 database contains 800 fingerprint images captured with size of 504 × 480 pixels. These fingerprint images was captured with a live scanner. The fingerprint recognition system implementation was done using Matlab 7.10.0 (R2010a) installed on computer Intel Core I5 Processor, 2.27GHZ, 3.00GB RAM, and windows 7 Service Pack 1. The selected 100 fingerprint images have been provided to the fingerprint recognition system. In the preprocessing stage, as possible the fingerprint image is enhanced using FDCT, segmentation, normalization, orientation & frequency estimation, and Gabor filter. Then the thinning step is performed to remove redundant pixels. In post processing stage, the features are extracted from fingerprint image, and false minutiae are removed. The last stage is the matching stage, the fingerprints features are converted to vectors, training, validation, and testing the network. After extensive and powerful training the system simulate the network to give an acceptable, robustness and proper recognition results. The characteristics of ANN used in the developed recognition system is given in table 2.

TABLE2 ANN CHARACTERISTICS

Characteristic	Value
Network type	feed-forward back propagation network
Number of network inputs	Size of input vector.
Number of layers	2
Number of neurons in hidden layer	150
Activation transfer function	Hyperbolic tangent sigmoid transfer function (tansig)
Weight and bias initialization function	By-weight-and-bias layer initialization function(initwb)
ANN training function	Scaled conjugate gradient back propagation (trainscg)
Average ANN learning rate	0.01 To 0.3
Average training epochs	200 To 2000
Performance function	Mean squared error with regularization performance function (msereg)

The ANN used in the experiment is shown in Fig. 11.

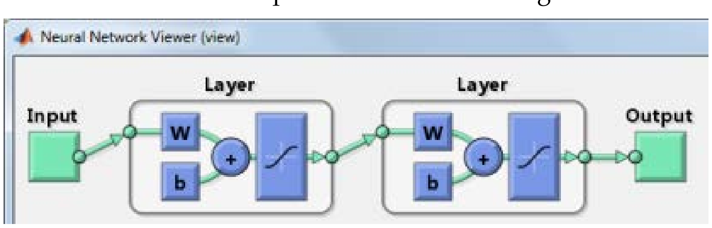

Fig. 11 Architecture of ANN using matlab.

In this experiment ANN network is trained through Feed-forward back propagation with scaled conjugate gradient algorithm. Fig. 12 displays the training progress of the network.

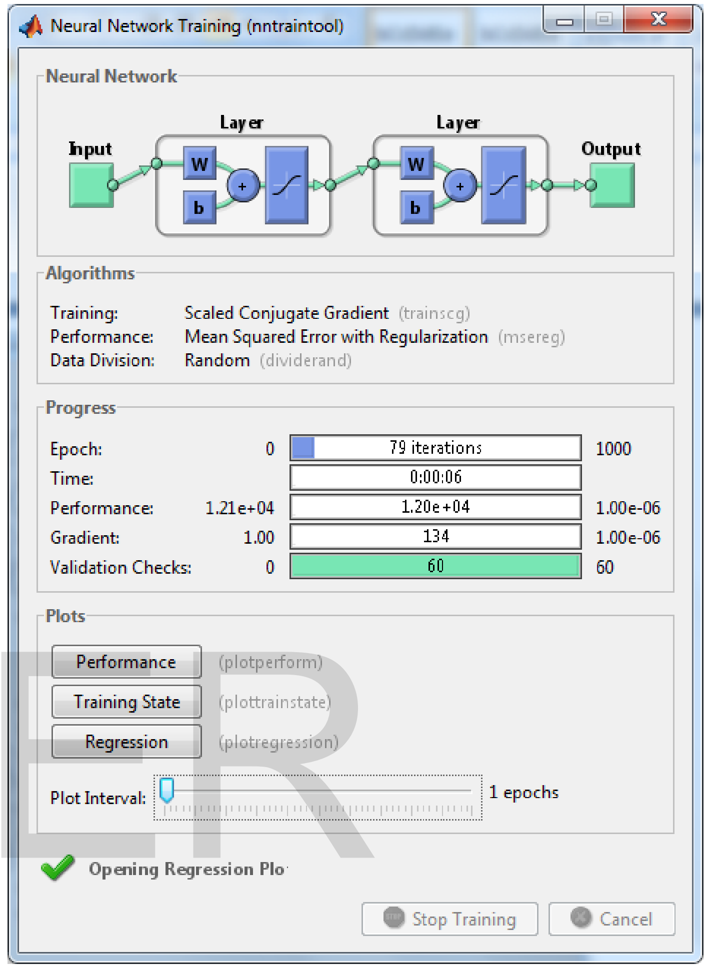

Fig. 12. ANN training result using matlab.

Training: It is used to adjust the network weights and biases according to its error (difference between actual network result & desired result).
Validation: It is used to measure network generalization, and to stop training when generalization stops improving.
Testing: It is used to test the final solution in order to confirm the actual predictive power of the network.
The regression of training is shown in Fig. 13.

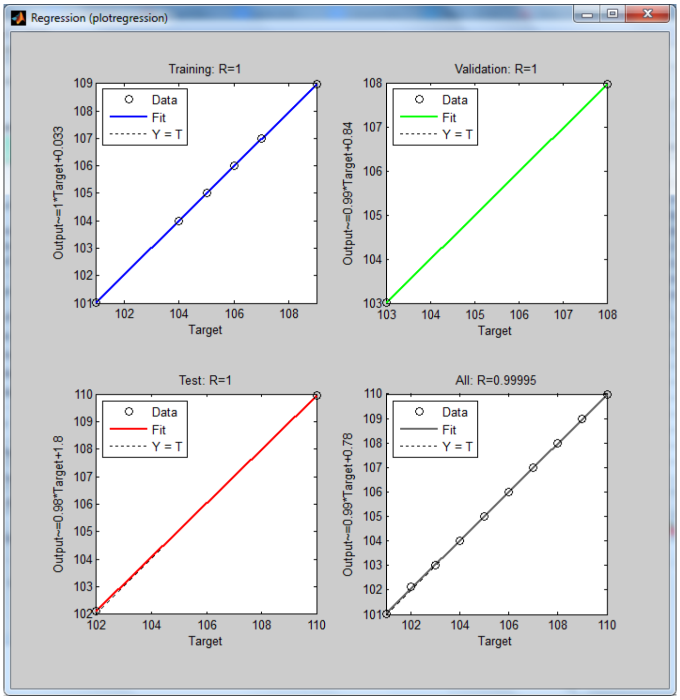

Fig. 13 Training regression result.

A part of the summary results (25-fingerprints images) of ANN-MDV recognition system is shown in Table 3.

TABLE3 25 FINGERPRINTS SAMPLES RESULTS USING (ANN-MDV)

Ser.	Sample	Actual result	Desired result	Recognized	time
1	'101_1'	101.0005	101	yes	2.767
2	'101_2'	101.0000	101	yes	0.126
3	'101_3'	101.0000	101	yes	0.119
4	'101_4'	101.0230	101	yes	0.118
5	'101_5'	101.0000	101	yes	0.119
6	'102_1'	101.6942	102	yes	0.119
7	'102_2'	101.0514	0	no	0.139
8	'102_3'	102.0987	102	yes	0.111
9	'102_4'	101.9553	102	yes	0.121
10	'102_5'	101.9540	102	yes	0.147
11	'103_1'	103.0208	103	yes	0.137
12	'103_2'	102.2903	0	no	0.103
13	'103_3'	103.4391	103	yes	0.098
14	'103_4'	102.8975	103	yes	0.123
15	'103_5'	103.0667	103	yes	0.108
16	'104_1'	104.4020	104	yes	0.112
17	'104_2'	103.9129	104	yes	0.115
18	'104_3'	104.0131	104	yes	0.118
19	'104_4'	104.6567	0	no	0.132
20	'104_5'	104.1761	104	yes	0.102
21	'105_1'	104.9157	105	yes	0.122
22	'105_2'	104.9223	105	yes	0.114
23	'105_3'	104.9001	105	yes	0.115
24	'105_4'	104.9806	105	yes	0.102
25	'105_5'	104.7726	105	yes	0.101
Number of recognized samples				22	
Average Recognition Time (ART)				0.223	

Also a part of the summary results (25 fingerprints) of fingerprint recognition system using ANN-PCA is given in table 4.

TABLE4 25 FINGERPRINTS SAMPLES RESULTS USING (ANN-PCA)

Ser.	Sample	Actual result	Desired result	Recognized	time
1	'101_1'	101.0429	101	yes	8.114
2	'101_2'	101.0234	101	yes	0.140
3	'101_3'	101.0791	101	yes	0.127
4	'101_4'	101.1516	101	yes	0.111
5	'101_5'	101.0207	101	yes	0.127
6	'102_1'	102.4475	102	yes	0.120
7	'102_2'	102.0903	102	yes	0.115
8	'102_3'	101.9638	102	yes	0.151
9	'102_4'	101.8559	102	yes	0.132
10	'102_5'	102.0132	102	yes	0.144
11	'103_1'	102.7172	103	yes	0.115
12	'103_2'	103.2023	103	yes	0.105
13	'103_3'	103.1490	103	yes	0.124
14	'103_4'	103.0129	103	yes	0.114
15	'103_5'	103.2390	103	yes	0.105
16	'104_1'	103.7986	104	yes	0.171
17	'104_2'	104.0175	104	yes	0.125
18	'104_3'	103.7794	104	yes	0.114
19	'104_4'	104.2732	104	yes	0.136
20	'104_5'	104.3713	104	yes	0.127
21	'105_1'	104.9766	105	yes	0.120
22	'105_2'	104.7305	105	yes	0.143
23	'105_3'	104.6441	105	yes	0.142
24	'105_4'	104.6865	105	yes	0.165
25	'105_5'	104.6308	105	yes	0.125
Number of recognized samples				25	
Average Recognition Time (ART)				0.449	

In the above tables the first column shows the serial number of samples, the second column is name of the sample, the third column represents the actual result given by the neural network simulation, and the fourth column shows the desired value of the output. The fifth column represents the recognition state; the last column is the value of average recognition time.

5 COMPARISON & DISCUSSION

A comparative study between the 2-developed recognition systems is done based on system accuracy and ART. Also this study explains the performance, effectiveness, and powerful of each recognition system. Table 5 represents a comparison between the 2 developed systems.

TABLE 5 COMPARISON BETWEEN ANN-MDV & ANN-PCA

Comparison parameter	ANN-MDV	ANN-PCA
Total number of fingerprints images	100	100
Number of recognized samples	91	98
Number of false recognized samples	9	2
Accuracy of the system	91%	98%
Average Recognition Time (ART)	0.2509	0.275

The accuracy of the system can be calculated by (6).

$$\textit{Accuracy of the system} = \frac{\textit{number of recognized samples}}{\textit{total number of stored samples}} \times 100\ \% \qquad (6)$$

Then the accuracy of ANN-MDV system is equal to: $91/100 \times 100 = 91\%$.

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Similarly the accuracy of ANN-PCA system is equal to: $98/100 \times 100 = 98\%$.
Therefore ANN-PCA system is much better than ANN-MDV system in terms of system accuracy.
Average recognition time can be calculated by (7).

$$\boldsymbol{Average\ recognition\ time} = \frac{sum\ of\ recognition\ time\ of\ all\ sample}{total\ number\ of\ stored\ samples} \qquad (7)$$

For ANN-MDV system: the recognition time is calculated for each fingerprint image, then the sum of these recognition times of 100 fingerprints images is estimated in order to compute ART which is equal to 0.2509.
In the same manner ART of ANN-PCA recognition system is equal to 0.275. Hence ANN-MDV system is slightly better than ANN-PCA in terms of ART.

6 Summary, Conclusion And Future Work

There are several ways of fingerprint recognition methods used to identify the person; we had developed two new effective fingerprint recognition systems ("ANN-MDV" & "ANN-PCA"). The traditional methods can't provide satisfactorily results in case of unavailability of some fingerprint's features. As mentioned above one of the major advantage of neural network (which is the core function of the two developed methods) its capability of predicting and identifying the person fingerprint when some features are not found. The previous explanation of PCA algorithm had stressed the fact that the main advantage of PCA is to compress data by reducing the matrix dimensions without losing much information, therefore reducing the size of fingerprint data base and results can be processed quickly. After discussion of the MDV algorithm we conclude that orientation direction of fingerprint image doesn't affect the performance of fingerprint recognition system. From the previous comparison table we conclude the following:

1. The system accuracy of the ANN-PCA is much higher than ANN-MDV.
2. ART of ANN- MDV is shorter than ANN-PCA.

Finally we concluded that ANN-PCA system is better than ANN-MDV system. Future work: we will use support vector machine SVM instead of neural network in order to improve fingerprint classification process. We can use circular Gabor filter with fast discrete curvelet transform FDCT to increase the efficiency of fingerprint image enhancement stage.

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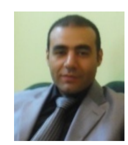
Authors

1- Eng**. Hany Hashem Ahmed** is currently pursuing masters degree program in Department of Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University, Egypt. E-mail: hhahmd@hotmail.com Phone: +201097100936.



2- Prof. **Hamdy M. Kelash** is Emeritus Professor in the Department of Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University. E-mail: HMK3947@yahoo.com.

3- Dr. **Maha S. Tolba** is lecturer in the Department of Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University. E-mail: maha_saad_tolba@yahoo.com.

4- Dr. **Mohammed Badawy** is lecturer in the Department of Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University. E-mail: MBMBadawy@yahoo.com.