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Comparative Study of Various Techniques of Fingerprint Recognition Systems

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Abstract: Nowadays Biometric plays vital role in many applications. It is defined as the credentials of people based on their physiological or behavioral characteristics. Biometric recognition can be classified into various types they are fingerprint, face, iris, palm print, voice, and DNA recognition. Among these fingerprint recognition plays major role since it do not change due to age factors, bruises cut, weather factor and so on. Various matching techniques used for fingerprint recognition systems such as minutiae based matching, pattern based matching, Correlation based matching, and image based matching. This paper focuses on features extraction and minutiae matching stage. 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 results. A comparative study among the various recognition systems is done based on Average Recognition Time (ART), False Acceptance Rate (FAR), False Rejection Rate (FRR), and the accuracy of the system. The experimental results are done on FVC2002 database using Matlab 7.10.0 (R2010a). The results show that the ANN-PCA system has the highest system accuracy (98%), lowest FAR, lowest FRR, and acceptable average recognition time. Therefore ANN-PCA is the best recognition system. Also the experimental results show that ANN-MDV system has shortest ART (0.251).

Keywords: Fingerprint Recognition, image enhancement, FDCT, MDV, ANN, BPN, PCA, FRR, FAR, ART

1. INTRODUCTION

Fingerprint recognition is one of the oldest and most popular biometric technologies, and it is used in criminal investigations, civilian and commercial applications and so on. Fig. 1 represents the popularity percent for each biometric technology.

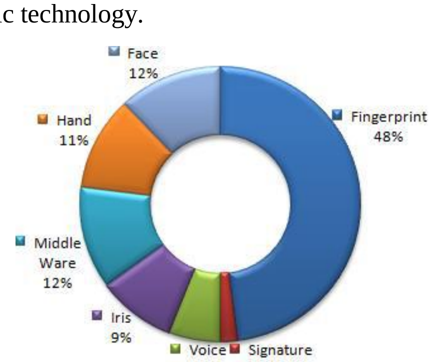

Fig.1 Comparative survey of fingerprint with other biometrics [1]

The major reasons for using fingerprints for identification and verification:

1. Availability for all individuals irrespective of race, gender or age.
2. Availability of easy, smooth operational and cheap fingerprint capturing devices.
3. Stability in pattern or form over time.
4. Fingerprint is distinct and highly unique from individual to individual.
5. Nowadays fingerprint sensors are cheaper and smaller, automatic fingerprint identification system (AFIS) has become popular alternatives or complements to related recognition techniques [1].

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

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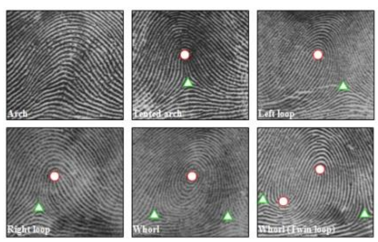
from the local discontinuities in ridge flow pattern. These minutiae have the required features that are used in fingerprint recognition system. There are many types of minutiae like Bifurcation, Termination, Lake, Spur, Crossover, dot, bridge, trifurcation, island, and singular points (core & delta). 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 [2, 3]. Fig. 2 shows the considered minutiae.

(a) Bifurcation (b) Termination



(c) Core & Delta points

Fig. 2 Types of minutiae

The technique used for the 2-proposed fingerprint recognition systems 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 used for the 2-proposed fingerprint recognition systems 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 proposed system. In fingerprint recognition system back propagation network is the best network in training and return relevant result. 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 follows: Section 2 discusses the principle of ANN, advantages of ANN, MDV definition and explains the work of PCA, and introduces the previous fingerprint recognition systems such as fingerprint matching using neighborhood distinctiveness, and minutiae extraction and pruning based fingerprint identification with pattern classification by radial basis function. Section 3 shows the figures of the 2-proposed systems and discusses the main stages of each one. Section 4 presents the performance metrics used to evaluate the proposed systems. Section 5 explains the operational environment of the recognition systems, shows the experimental results, and also tests the recognition systems. Also this section introduces a comparative analysis between the recognition regimes, and represents a comparison table. The last section gives a brief summary, conclusion, and represents short notes for future work.

2. Related Work

This section presents a survey on various important related fingerprint recognition systems. And also presents a description of neural network, principle component analysis, and minutiae distance vector.

A. 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.

B. Principle Component Analysis (PCA)

Due to great difficulties in determining similarities and differences between data arising from large patterns of data, PCA is used to solve this problem. PCA is an efficient and a powerful tool for analyzing data pattern. The 2^{nd} important advantage 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), those PCs are always less than or equal to the original related variables [4, 5].

C. 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 [6, 7]. ANN can be used to store and query data or pattern, classify pattern and find solution to constrained optimization problems. Fig. 3 shows a simple neuron [8].

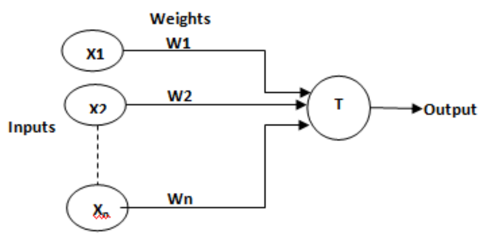


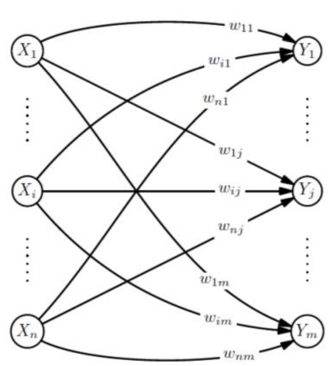
Fig. 3 Simple neuron or node.

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

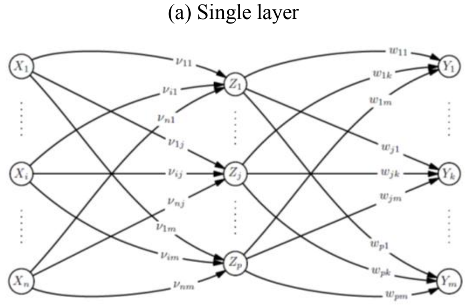
$$output = \begin{cases} 1 & if \ \sum_{i=1}^{n} wi \, . xi \quad \geq T \\ 0 & if \ \sum_{i=1}^{n} wi \, . xi \quad < T \end{cases} \qquad (1)$$

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 can be characterized by:

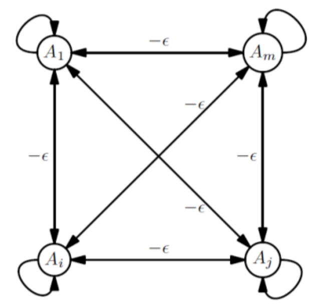
1- Architecture: as shown in fig. 4, it is patterns of connections among the neurons (arrangement of neurons into layer) [8].



(a) Single layer



(b)Multilayer



(c) Recurrent

Fig. 4 Neural network architectures

As shown in Fig. 4 there are three architecture types:

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.

2- Training or learning types: are methods to estimate the weights on the connections. Learning types are:

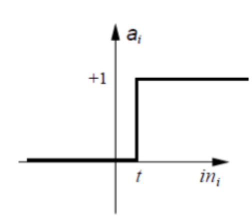
a. Supervised learning: each input vector of the network has an associated target output vector. Every learning cycle the error (difference between the actual and desired output) is used to adjust the weights.

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 function: it is used to determine how the output of the neuron will be calculated [8]. There are many activation functions, some of them are seen in fig.5.

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

(a) Binary step function with threshold t.



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

(b) Bipolar binary function.

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

(c) Sigmoid function.

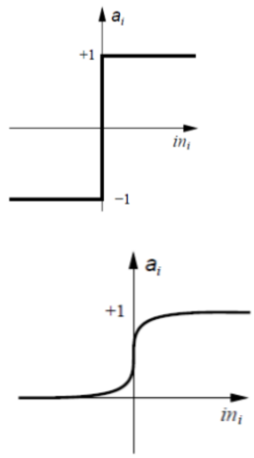


Fig. 5 Activation functions.

D. Fingerprint Matching using Neighbourhood Distinctiveness [1]

This recognition system is based on fingerprint pattern matching technique. The system takes the spatial characteristics on the 11 x 11 neighborhood of the fingerprint core points to calculate the matching scores. According to the matching score value the system can distinguish whether the two fingerprint images match or not. The conceptual diagram of this system is given in fig.6.

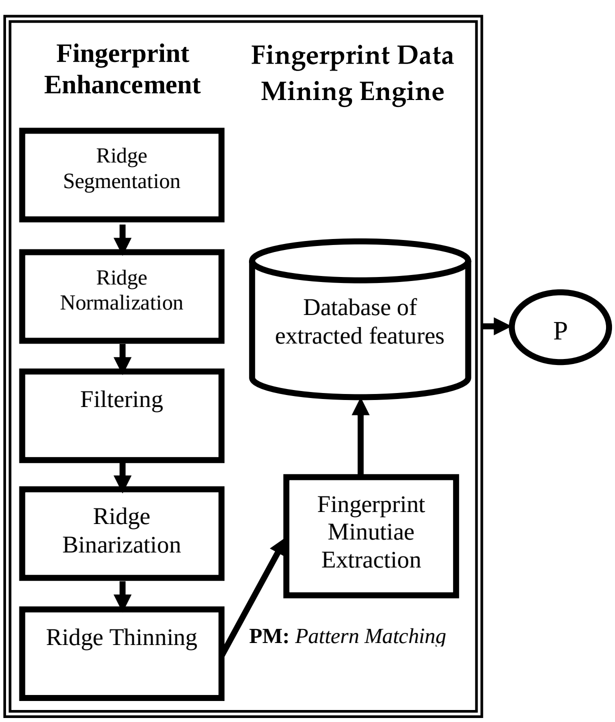


Fig. 6 Conceptual diagram of the system framework [1]

The conceptual diagram consists of 2-subsystems; the first subsystem is the fingerprint data-mining engine, which includes the following stages:

1. Fingerprint image enhancement: contains sub-module such as segmentation, normalization, filtering, noise removal, ridge binarization and thinning steps.
2. Fingerprint minutiae extraction: extracts the features from the enhanced fingerprint image
3. Extracted minutiae Database: has tables of related entities which contain fingerprint unique identification number, type, orientation, type of minutia among others, minutia x and y coordinate points.

The second sub-system is the pattern-matching which calculates the distances between the image reference (core or delta point) and the other features points neighbors. The algorithm of the pattern-matching module is in the following phases:

1. Find the fingerprint image core point.
2. Find the equations of the straight lines connecting all the feature points in the 11 x 11 neighborhood of the core point.
3. Calculate the locations of all interception points (junction points) between all possible pair of lines (by solving the two equations together)
4. The distance between each junction and the image core point is calculated by (5).

$$\omega i = ((e_i - \alpha)^2 + (f_i - \beta)^2)^{0.5} \quad (5)$$

Where:

e_i *and* f_i are the coordinates of junction.

α *and* β are the coordinates of the core point.

5. The degree of closeness γ_c, is calculated by (6)

$$\gamma_c = \sum_{i=1}^{n} \frac{|P(i) - I(i)|}{P(i)} \quad (6)$$

Where:

n is the smaller number of junction points in the query and stored image

P(i) and I(i) represent the distance between the i^{th} junction point and the core point for the query and stored image respectively

6. The cross-correlation coefficient value (C) is then computed as the pattern matching score for any two images by (7)

$$C = 100 * (1 - \frac{\gamma_c}{100}) \quad (7)$$

E. Minutiae Extraction and Pruning Based Fingerprint Identification with Pattern Classification by Radial Basis Function [9]

The design of this system is shown in fig. 7.

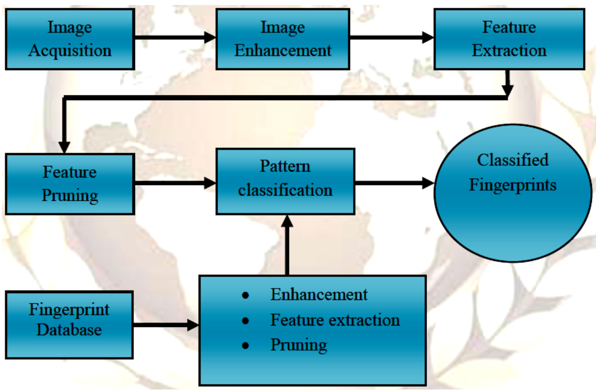


Fig. 7 Block diagram of fingerprint identification system [9].

The stages of this system are:

1. Image acquisition: the fingerprints images are taken from FVC2002 database (100 fingerprints images).
2. Image enhancement: in this stage, the operations done on the fingerprint images are filtering, binarization and thinning.
3. Features Extraction: the termination points and bifurcation points are extracted in this stage using crossing number technique
4. Features Pruning: the main purpose of this stage is to extract the redundant features and to keep the important details in fingerprint.
5. Pattern Classification: this system uses pattern based matching algorithm in which the given pattern first is classified by radial basis function network, and then a decision is made whether the input fingerprint is matching with the template stored in the database or not.

3. Proposed System

Two systems are proposed as follow:

3.1 First: *Fingerprint Recognition System using ANN based on MDV [10].*

The flow chart of the first fingerprint recognition system using ANN based on MDV is shown in fig. 8.

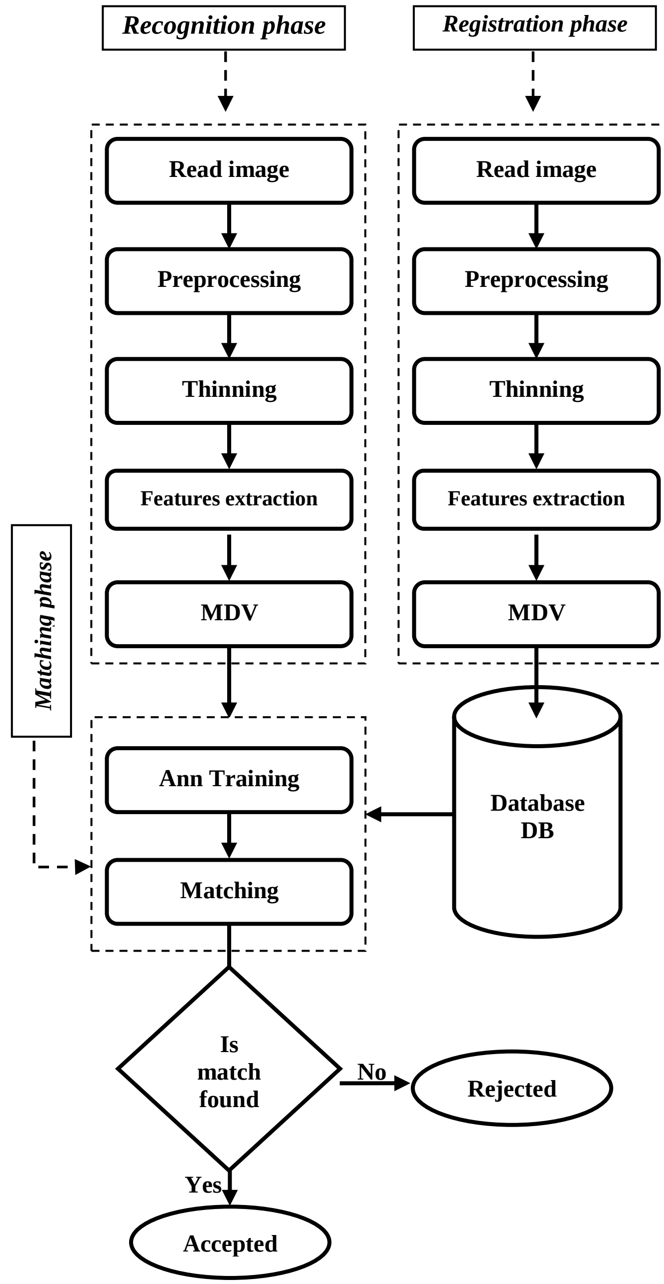


Fig. 8 Flow chart of ANN-MDV system [10]

As shown in fig. 8 the recognition system has 2-phases:

Registration phase: In this phase, the minutiae are extracted from fingerprint image. These features are converted to MDV vector. Finally this vector is stored as a template in the enrollment database.

Recognition phase: Also in the identification phase, the MDV vector for the query fingerprint image is obtained in the same manner as explained in the registration phase.

Matching phase: The neural network is trained and tested using the MDV vectors stored in the enrollment database. After a powerful neural network training, the network simulates and matches the MDV vector of the query fingerprint image obtained from the recognition phase with the stored templates in the enrollment database. Finally the system gives the matching result, and the decision to accept or reject the input fingerprint.

The stages of ANN-MDV recognition system are:

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 the preprocessing step 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 [10]:

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 is 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).

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.

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

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

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.

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

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 is very easy.

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. 9. 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.

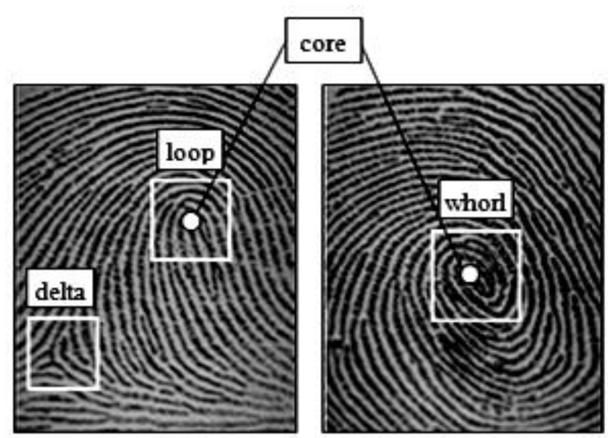


Fig. 9 a core and a delta singularity in a right loop fingerprint

The algorithm used for extracting features from fingerprint image is Crossing Number (CN) which consider (3x3) pixel window as shown in fig. 10

P4	**P3**	**P2**
P5	**P**	**P1**
P6	**P7**	**P8**

Fig. 10 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).

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

Where P_i is the pixel value in the neighborhood of P.

The pixel can be classified according to the value of CN as shown in table 1 [11, 12].

TABLE1 MINUTIAE CLASSIFICATION

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

<u>Remove false minutiae:</u> 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.

<u>Direction and angle of correct minutiae:</u> 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
End if [13].
```

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.

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. 11.

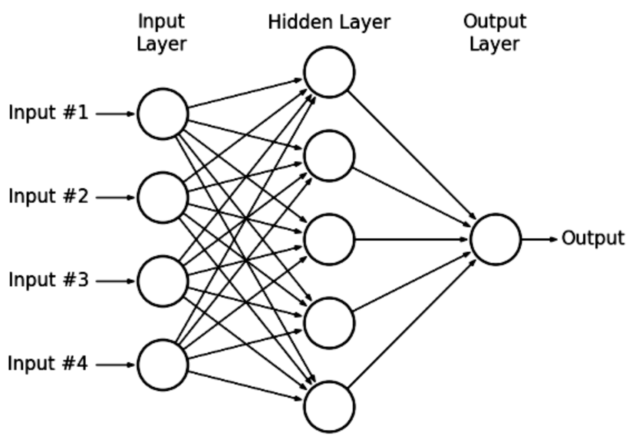


Fig. 11 Structure of back propagation neural network [8]

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 proposed 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 [8]:

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 [14].

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 [14].

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 Second: *Fingerprint Recognition System using ANN based on Principal Component Analysis [10].*

The block diagram of the second fingerprint recognition system is shown in fig. 12. The main difference between the 2-proposed systems is in stage 3 (PCA).

The steps of the second algorithm are:

Step 1. Preprocessing of the first proposal.

Step 2. Feature extraction: As mentioned before.

Step 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 proposed 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.

Step 4. Ann training: As mentioned before.

Step 5. Ann testing: As mentioned before.

Step 6. Matching: As mentioned before.

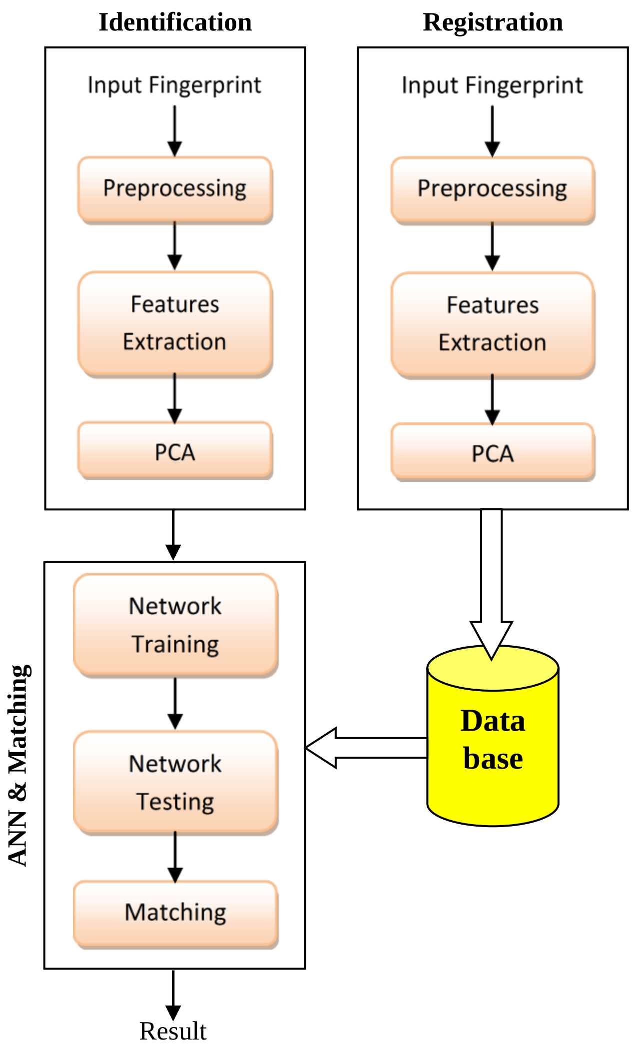


Fig. 12 Fingerprint recognition ANN-PCA [10]

4. PERFORMANCE METRICS

In order to make a comparative study among the aforementioned recognition techniques, the following performance metrics will be used:

1. False Acceptance Rate (FAR) [15]: It is the rate which non-authorized persons are falsely accepted as authorized persons. The recognition system with low value of FAR is considered to be favorable one. FAR is given by (9).

$$FAR = \frac{No.of\ non - authorized\ persons\ accepted \times 100}{Total\ number\ of\ non - authorized\ comparison} \quad (9)$$

2. False Rejection Rate (FRR) [15]: It is the rate of frequency that authorized persons are falsely rejected as non-authorized persons. The recognition system with low value of FRR is considered to be favorable one. FRR is computed by (10).

$$FRR = \frac{No.of\ authorized\ persons\ rejected \times 100}{Total\ number\ of\ authorized\ comparison} \quad (10)$$

3. Accuracy of the system [10]: it can be estimated by (11).

$$System\ Accuracy = \frac{No.of\ recognized\ samples}{total\ No.of\ stored\ samples} \times 100\ \% \quad (11)$$

4. Average Recognition Time (ART) [10]:

   ART can be calculated by (12).

$$ART = \frac{sum\ of\ recognition\ time\ of\ all\ sample}{total\ number\ of\ stored\ samples} \quad (12)$$

5. COMPARATIVE RESULTS OF THE VARIOUS TECHNIQUES

This section presents the comparative results among Iwasokun Gabriel Babatunde in March 2013 [1], Nisha Negi Aug 2013[9], ANN-MDV and ANN-PCA.

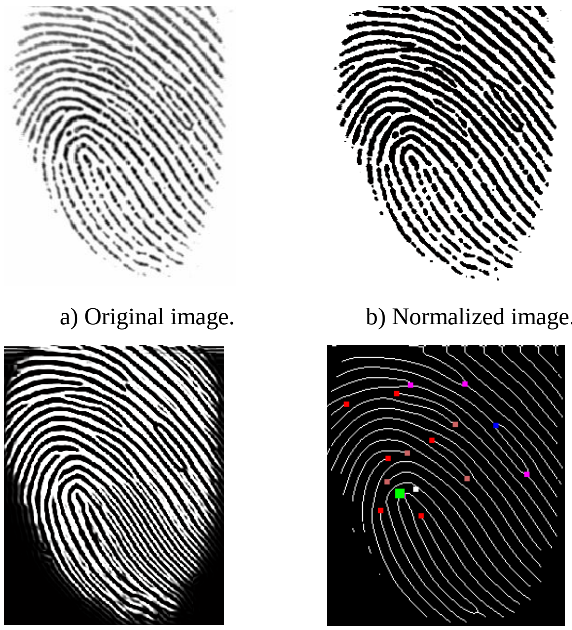
5.1 *Operational Environment*

The operational environment specifications can be characterized as:

1. Computer specifications: the Central Processing Unit (CPU) is Intel Core I5 Processor – 2.27 GHZ, the Random Access Memory (RAM) is 3.00 GB, and the Platform is windows 7 Service Pack 1.
2. Matlab specifications: The implementation of fingerprint recognition techniques was done using Matlab 7.10.0 (R2010a).
3. Database specifications: In the experimental results samples of fingerprint images of size 480 × 640 with 500dpi resolution are derived from FVC2002 database (http://bias.csr.unibo.it/fvc2002/download.asp) accessed in 15-01-2013 [16]. These fingerprints are taken with the help of optical sensor. FVC2002 database contains four different qualities datasets DB1, DB2, DB3, and DB4. 25-fingerprint images are taken from each dataset (5 persons each with 5 impressions).

5.2 *EXPERIMENTAL RESULTS FOR THE 2-PROPOSED SYSTEMS*

The selected fingerprint images have been provided to the fingerprint recognition system. In the preprocessing stage the noise is removed using fast curvelet, perform segmentation, normalization, estimate the orientation & frequency, and apply Gabor filter. Then the thinning step is applied to remove redundant pixels. In the features extraction stage, the features are extracted from fingerprint image, and false minutiae are removed. Fig. 13 presents some steps of preprocessing stage, and shows the features of the thinned fingerprint image.



a) Original image. b) Normalized image.

c) Final enhanced image. d) Fingerprint features.

Fig. 13 Preprocessing & Features Extraction stages [10]

Finally in the last stage (matching stage), the minutiae of each image is converted to a vector, 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. In this experiment ANN network is trained through Feed-forward back propagation with scaled conjugate gradient algorithm. The characteristics of ANN used in the 2-proposed recognition systems is given in table 2 [10].

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	100 To 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 characteristics of training step:

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.

Fig. 14 shows the training progress of the network.

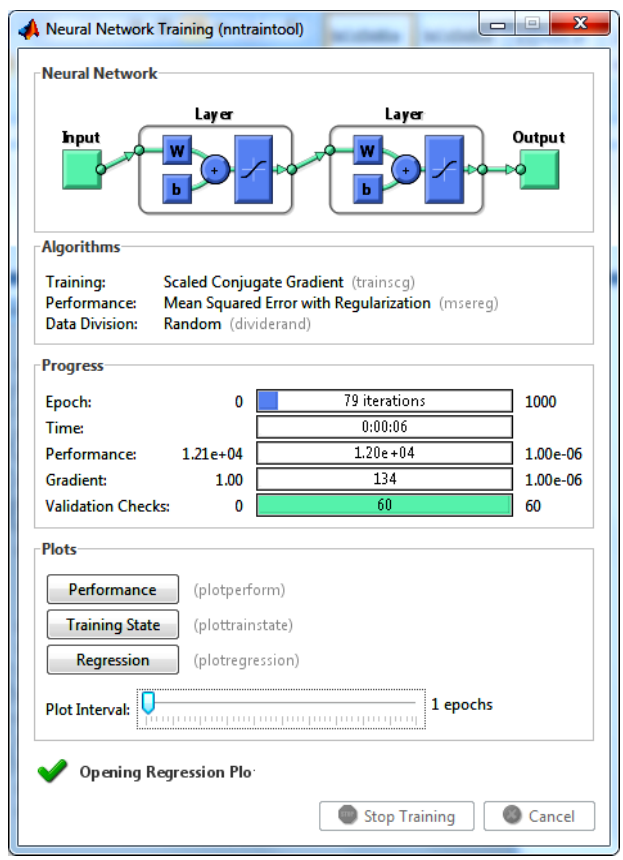


Fig. 14 ANN training result using matlab [10]

Fig. 15 displays the regression of the training step and measures the quality of training. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. As shown in fig. 15 the training measurement (training "R close to 1", validation "R close to 1", and test "R close to 1") which indicates that the network is trained very well and the classification of the network will give an excellent and robustness results.

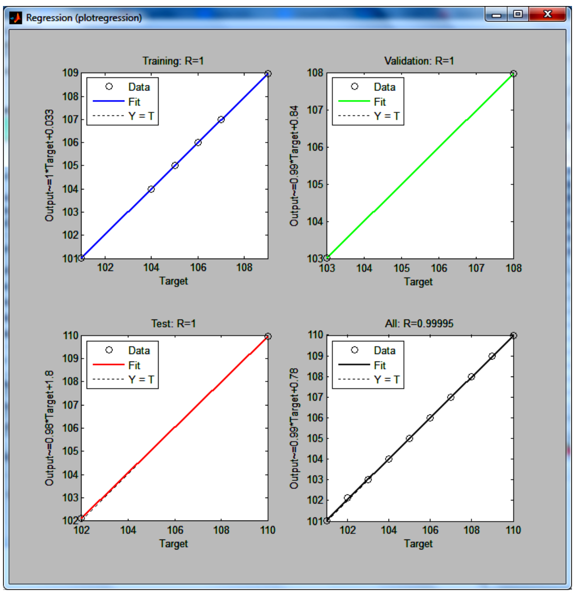


Fig. 15 Training regression result [10].

The experimental results for ANN-MDV system show that the ART value of 0.2509, FRR value of 9%, and the accuracy of system equal to 91%. Also the results for ANN-PCA system represent that ART value is 0.275, FRR is 2%, and system accuracy is 98%.

5.3 Comparative Study & Performance Analysis

Table 3 represents a comparison table among the recognition techniques after implementation of these techniques in the discussed operational environment.

TABLE3 Comparison among various recognition techniques

Comparison parameter	**Ref. [9]**	**Ref. [1]**	**ANN-MDV**	**ANN-PCA**
Number of persons	20	20	20	20
Number of impressions per finger	5	5	5	5
Total number of fingerprint samples	100	100	100	100
Number of recognized fingerprints	97	84	91	98
Number of false non matching fingerprints	3	16	9	2
Number of false matching fingerprints	null	null	null	null
FRR	3%	16%	9%	2%
FAR	null	null	null	null
Accuracy of the system.	97%	84%	91%	98%

Table 3 shows that the second proposed recognition system (ANN-PCA) is the best recognition system since it has the highest system accuracy, lowest FRR, and lowest FAR. The column chart of Accuracy system & FRR for the various recognition techniques is presented in fig. 16

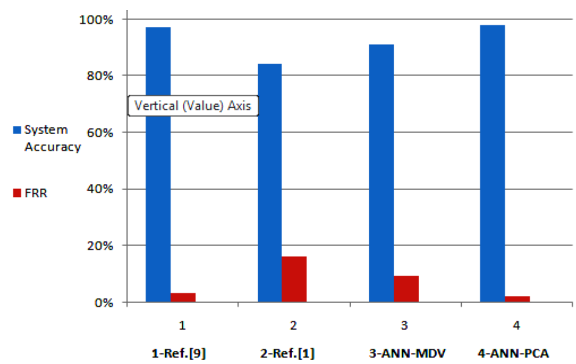


Fig. 16 Column chart of the System Accuracy & average FRR.

The comparative study examines the FAR, and FRR for each dataset (DB1, DB2, DB3, and DB4) which explained in table4.

TABLE 4 FRR & FAR for Different Algorithms

	Ref.[9]		**Ref.[1]**		**ANN-MDV**		**ANN-PCA**	
Dataset	***FRR***	***FAR***	***FRR***	***FAR***	***FRR***	***FAR***	***FRR***	***FAR***
DB1	8%	null	15.5 %	null	4%	null	4%	null
DB2	null	null	12.5 %	null	4%	null	null	null
DB3	4%	null	20.7 %	null	16%	null	4%	null
DB4	null	null	14.6 %	null	12%	null	null	null
Average FAR	null		null		null		null	
Average FRR	3.00%		15.82%		9.00%		2.00%	

From table 4 the 2-proposed systems have the smallest FRR in DB1. Reference [9] and the 2nd proposed system

ANN-PCA have the smallest FRR in DB2, DB3 and DB4. Therefore the second proposed system ANN-PCA has the smallest average FRR & FAR, so that it is the best algorithm in terms of FAR & FRR. The column chart of the FRR trend for the four datasets is presented in fig. 17

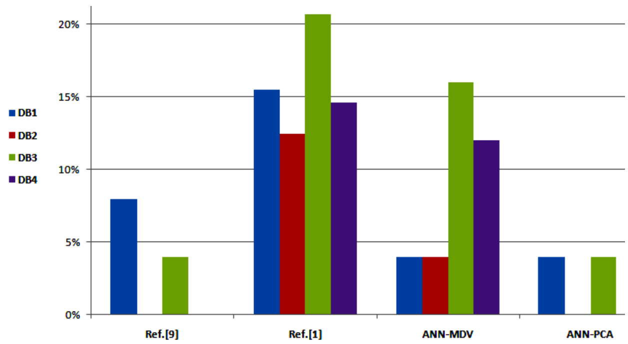


Fig. 17 Column chart of FRR values for the four dataset.

After implementation of the previous recognition techniques, Table 5 introduces a comparative study table among these techniques based on average recognition time ART for each dataset.

TABLE 5 MATCHING TIME FOR DIFFERENT ALGORITHMS

	Ref.[9]		Ref.[1]		ANN-MDV		ANN-PCA	
Dataset	***FRR***	***FAR***	***FRR***	***FAR***	***FRR***	***FAR***	***FRR***	***FAR***
DB1	0.49	0.66	0.61	0.69	0.22	0.43	0.45	0.32
DB2	0.47	0.54	0.49	0.59	0.16	0.25	0.17	0.30
DB3	0.47	0.57	0.81	1.07	0.16	0.25	0.17	0.31
DB4	0.47	0.56	0.69	0.79	0.26	0.27	0.17	0.31
ART of FAR	0.5809605		0.785		0.3018735		0.3113325	
ART of FRR	0.4745		0.65		0.2		0.2384	
ART	0.5277303		0.7175		0.2509368		0.2748663	

Table 5 shows that the 2-proposed systems have the smallest ART for each dataset. ART of The first proposed system ANN-MDV is slightly shorter than the second proposed system ANN-PCA, so that the first proposed system is the best system in terms of ART. The column chart of ART for the recognition techniques is shown in fig. 18

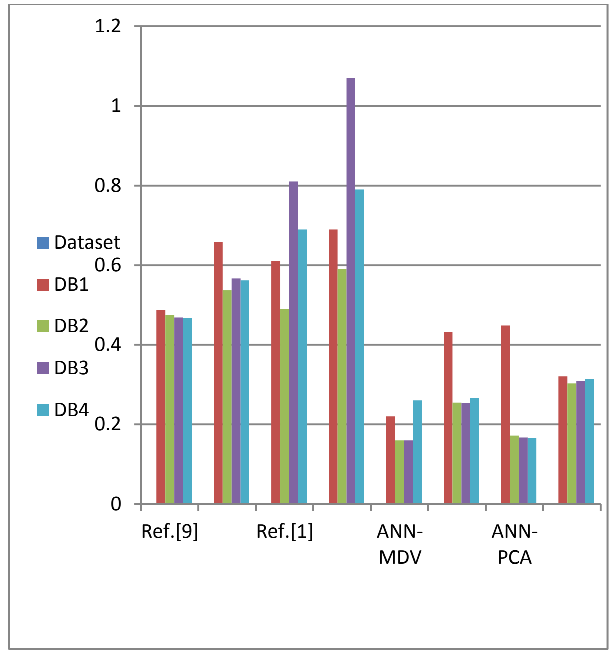


Fig. 18 Column chart of ART values for the four dataset.

6. CONCLUSION

There are several ways of fingerprint recognition methods (as in [1], and [9]) used to identify the person; Two new effective fingerprint recognition systems are proposed (first proposed system "ANN-MDV" & second proposed system "ANN-PCA"). The related recognition techniques 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 proposed methods) its capability of predicting and identifying the person fingerprint when some features are not found. After implementation of the proposed ANN, it has been concluded that the proposed network has best training (training "R≈1", validation "R≈1", and test "R≈1") which means that the network simulation output best results [10].

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 figures and comparison tables:

1. ANN-PCA has the smallest FAR (0.00%)
2. ANN-PCA has the smallest FRR (2.00%)
3. The ANN-PCA is the highest accuracy of recognition system (98.00%)
4. ANN-MDV system has the best ART (0.2509).

Finally we concluded that the second proposed ANN-PCA system is the best one in terms of FAR, FRR, system accuracy, and has an acceptable ART. Also the first proposed system ANN-MDV is the best recognition system in terms of ART, and has an acceptable system accuracy, FAR, and FRR.

In the future work: support vector machine SVM will be used instead of neural network in order to improve fingerprint classification process. Circular Gabor filter will be applied with fast discrete curvelet transform FDCT to increase the efficiency of fingerprint image enhancement stage. The second proposed algorithm ANN-PCA is suggested to be imbedded in various banking system to increase security.

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