Fingerprint Recognition Using Gabor Filter with Neural Network

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ABSTACT

The automated classification and matching of fingerprint images has been a challenging problem in pattern recognition over the past decades. This paper proposes a method to detect the rotation region based on Estimate Global Region (EGR) that has the maximum rotation region. The Gabor filter based feature is applied for extracting fingerprint features from gray level images without preprocessing. The fingerprint recognition is developed by neural networks with adaptive learning rate. The paper contains a comparison between using EGR algorithm and without using EGR. The Gabor filter without EGR gives the best result for the fingerprint recognition with outrotation while the rotation of the fingerprint with angles (5°,10° and 20°) gives worse results in fingerprint recognition. The proposalmethod gives best result in rotation the fingerprint image with and without the rotation of the same angles. The result of the correlation for the proposalmethod is 99%.

Keywords: Biometrics, fingerprint image, Gabor filter, Estimation Global Region, NN with adaptive learning rate.

تمييز بصمة الابهام باستخدام مرشح كابور مع الشبكات العصبية

الخلاصة

التصنيف الالي و مطابقة صورة بصمة الابهام في تمييز النماذج لا تزال مستمرة البحث من القرون الماضية. هذا البحث اقترح طريقةلكشف منطقة التدوير اعتمادا على (EGR) التي تحدد اكبر منطقة لتدوير بصمة الابهام. مرشح Gabor يطبق لاستخلاص صفات البصمة لصور المستوى الرمادي بدون معالجات اولية و لغرض التصنيف استخدمت الشبكة العصبية من النوع متعدد الطبقات ذات التعليم المتكيف. تضمن البحث مقارنة بين استخدام تخمين منطقة التدوير وبدون استخدام الخوارزمية وتبين من خلال النتائج ان استخدام مرشح Gaborبدون الخوارزمية يمطي نتائج ممتازة في تصنيف النماذج ولكن

للحالات التي لا يحدث فيها تدوير للبصمة . اما اذا حدث تدوير للبصمة بزوايا   °5, °10, °20 فان مرشحGabor سيعطي نتائج سيئة في التصنيف. الطريقة المقترحة اعطت نتائج ممتازة بوجود وبعدم وجود تدوير للبصمة و لنفس الزوايا للحالة السابقة . كما ان نتائج   correlation للطريقة المقترحة كانت 99% .

INTRODUCTION

Fingerprint technique is one of the most reliable biometric technologies. In fingerprint recognition, preprocessing such as smoothing, binarization and thinning are needed. Then fingerprint minutia feature is extracted [1].Many preprocessing steps and feature extraction processes have to be implemented before fingerprint image can be applied on matching algorithm[2]. Gabor filter based features have been successfully and widely applied to face recognition, pattern recognition and fingerprint enhancement. The family of 2-D Gabor filters was originally presented by Duagman as a framework for understanding the orientation and spatial frequency selectivity properties of the filter. Daugman mathematically elaborated further his work in [3]. In a local neighborhood the gray levels along the parallel ridge and valleys exhibit some ideal sinusoidal shaped plane waves associated with some noise [4]. Lee and Nam in [5] introduces an algorithm for fingerprint identification with simple preprocessing and low cost by wavelet based algorithm. Wam in [1] present a fingerprint recognition system that can match the fingerprint image based on feature extraction in the wavelet transform domain. Wam develop a low cost system since it does not require a lot of redundant work on preprocessing. [12]Propose a novel algorithm for singular point detection based on fingerprint orientation field reliability. [13] this paper proposes a novel method to consistently and precisely locate the singular points in fingerprint images. The method applied is based on the enhanced finger printimage orientation reliability.

In this paper, the rotation region is detected for each fingerprint image based on estimation global region (EGR) algorithm. Gabor filter for 16*16 non overlapping windows is used to extract the fingerprint features without any preprocessing. The classifications of fingerprint are developed by back propagation neural network algorithm with adaptive learning rate.

PROPOSED ALGORITHM

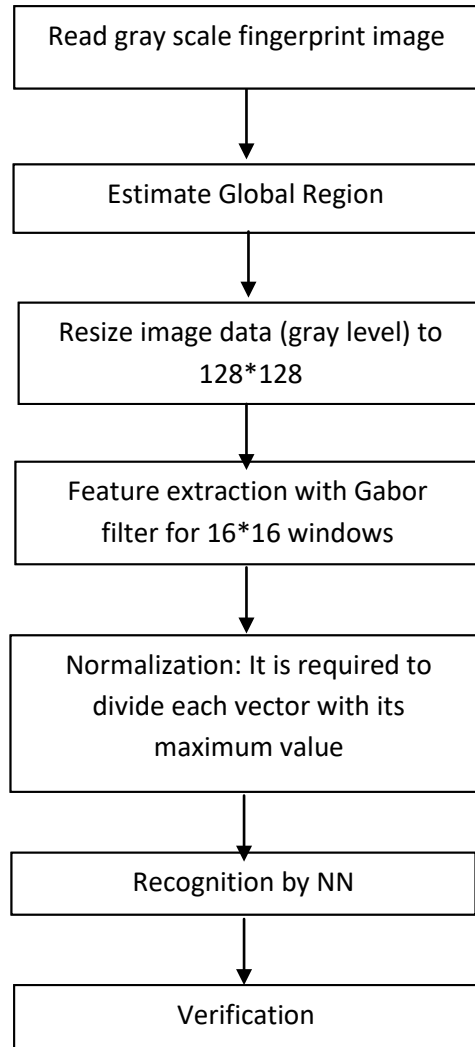The proposed method of fingerprint recognition system is shown in Figure (1)

Figure (1) block diagram of proposed algorithm.

ESTIMATION GLOBAL REGION ALGORITHM (EGR)

The procedure of EGR algorithm is elaborated in the following

1. the image generated by the scanner may be slightly different during each scan
2. The horizontal and vertical gradients $Gx(x, y)$ and $Gy(x, y)$ at each pixel (x,y) respectively are computed using Sobel filterfor window w=3*3.
3. Estimate the global orientation by computing the ridge orientation of each pixel (x,y) by averaging the squared gradients within a $W \times W$ window centered at [xi,yj] as in [12]

$$G_{xx} = \sum_{(x,y)\in w} G_x^2(x,y) \qquad \qquad \text{... (1)}$$

$$G_{yy} = \sum_{(x,y)\in w} G_y^2(x,y) \qquad \qquad \text{...(2)}$$

$$G_{xy} = \sum_{(x,y)\in w} G_x(x,y).G_y(x,y) \qquad \qquad \text{...(3)}$$

$$\theta(x,y) = \frac{1}{2}\tan^{-1}(\frac{2G_{xy}}{G_{xx}-G_{yy}}) \qquad \qquad \text{...(4)}$$

4. Estimate the global region by specifing the rotation of the pixel by computing the maximum θ(x,y), then find the pixels that have the maximum rotation according to

$$m_r = c * max\theta \qquad \qquad \text{...(5)}$$

Where maxθ=maximum θ(x,y)
c=controller value

5. Estimate the center of rotation region by sum the locations of these pixels and averaging these locations for each x,y
6. Take window nighboor the center of rotation region by $\pm r$
7. Construct the new image (obtianedfrom step 5) and resize the image to 128*128
8. Divide the image obtained from step 6 into a set of 16*16 non-overlapping windows, then apply Gabor filter for each window to get 16*16 features for each image. Then the Gabor feature matrix is converted to one dimension and normalized the vector by its maximum value of each vector. To reduce the size of storagedata and to increasedthe speed of training NN.
9. Use of neural networks as a possible solution for the case of fingerprint matching. Neural networks are trainable with adaptive learning rate.

GABOR FEATURE EXTRACTION
   Gabor filter optimally captureboth local orientation and frequency information from a fingerprint image. By turning a Gabor filter to a specific frequency and direction, the local frequency and orientation information can be obtained [6], [7]. Thus, they are suited thesefilters for extracting texture information from images [8].
Gabor filter has the general form in the spatial domain

$$h(x,y,\theta_k,f,\delta_x,\delta_y) = exp\left[-\frac{1}{2}\left(\frac{x_{\theta k}^2}{\delta_x^2} + \frac{y_{\theta k}^2}{\delta_y^2}\right)\exp(i2\pi fx_{\theta k})\right] \qquad \text{... (6)}$$

Where:
- $x_{\theta_k} = xcos\theta_k + ysin\theta_k$
- $y_{\theta_k} = -xsin\theta_k + ycos\theta_k$
- f is the frequency of the sinusoidal plane, It is set as $f = 1/2\sqrt{2}$
- θ is the orientation of the Gabor filter

- σ_x and σ_y are the standard deviations of the Gaussian envelope along the x and y axes
- The standard deviations σ_x and σ_y are determined empirically. In [9] $\sigma_x = \sigma_y = 2$ was used so in this paper. While different value are used in [14] as $\sigma_x = \sigma_y = 4$ and $f = 1/5$

The number of orientation is specified by m.where $\theta_k = \pi(k-1)/m$, where k=1… m
Rewrite the equation(6) in complex form giving

$$h(x,y) = h_{even} + i.h_{odd}$$

$$h_{even}(x,y) = \exp\left[-\frac{1}{2}\left(\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right)\right]\cos(2\pi f x_{\theta_k})$$

$$h_{odd}(x,y) = \exp\left[-\frac{1}{2}\left(\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right)\right]\sin(2\pi f x_{\theta_k})$$

... (7)

After deciding the parameter of the Gabor filter, the magnitude Gabor feature at sampling grey point(x,y) can be obtained as

$$\text{Gmag}(x,y,\theta_k,f,\delta_x,\delta_y) = \sum_{x=-w/2}^{\frac{w}{2}-1}\sum_{y=-w/2}^{\frac{w}{2}-1} I(X+x,Y+y)\,h(x,y,\theta_k,f,\delta_x,\delta_y)$$

… (8)

NEURAL NETWORK WITH ADAPTIVE LEARNING RATE

One of the most important things in training a neural network is its learning speed because the training process generally takes much time. The learning speed of the network greatly depends on the value of the learning rate. However, it is very difficult or even impossible to find the optimal learning rate for a neural network. [10]

There is a computational technique to work out network errorso that the learning rate can be computed. This is achieved by computing the error for each layer based on which the differential of the error for each layer may be determined. In fact instead of changing the delta error, the learning rate for the whole layer for which the error was computed is changed. Ineach iteration the learning rate is updated according to the error of the layers. The assumption is that each layer has a varying learning rate which needs to be updated ineach iteration. While the error in adjusted deferential adaptive learning rate (DALRM) will be as*:*

$$\alpha_{out} = \dot{f}(|target - output|) \qquad \text{… (9)}$$

Where *f* is an activation function
The algorithm is presented in [11]

Input unit: $x_i = (i = 1,2,3, \ldots\ldots n)$ where input vector n=64 (in our proposal algorithm)
Hidden unit: z_j=(j= $i = 1,2,3, \ldots\ldots p$) where p=40

Step 1: initialize weights, compute the network output for each training pair , in our proposal,the number of nodes for output layer =7

$$Z\_inf = V_{oj} + \sum_{i=1}^{n} X_i V_{if}$$

$$Z_f = f(Z\_inf)$$

$$y_{in_k} = w_{ok} + \sum_{i=1}^{p} Z_j W_{jk} \qquad \ldots (10)$$

$$y_k = f(y\_in_{k)}$$

Step 2: for each layer, compute the error (backward)

$$\delta_k = (t_k - y_k) f(y'_{-in_k}) \qquad \ldots (11)$$

Compute the learning rate for output layers:

$$\alpha_{out} = \acute{f}(|t_k - y_k|) \qquad \ldots (12)$$

Compute the weight changes withnew learning rate:

$$\Delta W_{jk} = \alpha_{out} \delta_k Z_j$$
$$\Delta W_{ok} = \alpha_{out} \delta_k$$
$$\delta_{-in_j} = \sum_{k=1}^{m} \delta_k W_{jk} \qquad \ldots (13)$$
$$\delta_f = \delta_{-inf} \acute{f}(Z_{in_f})$$

for hidden layers , the learning rate:

$$\alpha_{hid} = \acute{f}(1/h_{number} \sum_{j=1}^{p} \delta\_in_f) \qquad \ldots (14)$$

Compute the weight changes with new learning rate:
$$\Delta V_{if} = \alpha_{hid} \delta_i x_i$$
$$\Delta V_{oj} = \alpha_{hid} \delta_j \qquad \ldots (15)$$

Update the weights as

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk}$$
$$V_{tf}(new) = V_{tf}(old) + \Delta V_{tf} \qquad \ldots (16)$$

Step 3: repeat step 1-3 whilst stopping condition is false

SIMULATION RESULTS
We have tested the performance of the proposed algorithm of a databases consists of eight fingerprint images.

The spatial resolution used in scanning process was 500 dpi, andamplitude resolution was 256 gray levels (8 bits per pixel).

The simulation contains two partitions part A: implement the Gabor feature extraction for 8*8 and 16*16 windows that relates to the same person then 16*16 Gabor feature extraction for deferent person are developed without EGR. the magnitude Gabor feature extraction for 8*8 is computed for different angle as computed by equation (8) for the same person but with small noise as shown in Figure (2.a) ,Figure (2.b) from these feature extraction we can see that Figure (2.c) is the same as Figure (2.d) for the same angle (Ө=0). Figure (2.e) is the same as Figure (2.f) for the same angle (Ө=45). And so on for the other angles.

In Figure (3), Gabor magnitude feature is computed for 16*16 windows. The same procedure of Figure (2) is done for Figure 3 in which the magnitude Gabor feature is applied for the same person and for four angle Ө=0, 45, 90, 135. We can see from this figure that the feature obtained is the same for the same angle as shown in Figure (3.c) , (3.d) for Ө=0 and the same for other angles. From Figures (2,3) we notice that the feature obtained from Gabor filter is the same even in the presence of the noise). While the difference between two figures is that the Gabor magnitude feature with 16*16 windows can be obtained with small size.

In Figure 4, magnitude Gabor feature extraction of 8*8 window is applied for two different person, we can see that the features is different for the same angle as shown in Figure (4.c),Figure (4.d) with θ=0 and so on for others angles.

The result of Figure 2,3,4 is illustrate the application of magnitude Gabor features with 8*8 windows and 16*16 windows for the same person and different persons in the absence of the noise without using our proposal.

Part B: include the implementation of the proposal algorithm that depicted in section 3, the fingerprints obtained from the EGR are shown in Figure (5). This Figure contains 7 fingerprint images for different person as Figure.5 (1-7). And 3 fingerprint for the same person but with rotation angle ($5^o, 10^o, 20^o$) as shown in Figure.5 (8-10). The proposal algorithm estimates the maximum rotation region. Choosing c=0.8 (controller) in equation (5) in order to include the center of rotation and its nearest region of rotation. The fingerprint image obtained is of size 60*60; this image contains the maximum rotation region in the fingerprint image as shown in Figures (1-10). After applying the EGR , the fingerprint images in Figures (1-10) will be resize to 128*128, the magnitude Gabor feature for 16*16 non overlapping window is performed , then for each fingerprint image there are 64 features extraction as the output of Gabor filter and represent the input pattern .

The number of inputof NN equal to the element of vectors. The output target equalthe number of images, while the hidden layer =2*input -1/2. (the number of hidden layer=40,the number of nodes for output layer =7 and the number of nodes forinput layer =64).The training phase of the NN is shown in Figure(6). The testing phase of the NN without using EGR algorithm is shown in Table(1), in this table we can see that the recognition using Gabor feature extraction is high performance for the same pattern while for fingerprint rotation with the previous angles, its performance is worst. In Table (2), the EGR algorithm is used for Gabor filter extraction to recognize the fingerprint image with rotation by angle$5^°, 10^°, 20^°$and without rotation. The proposed algorithm gives best

result in recognition the pattern 1 for different rotation as shown in Figure 7,in which the mean square error is used between outputof NN in testing phase and target with and without the features of the EGR.

The result of the recognition is done by usingcorrelation measurements as defined [14]:

$$Corr. = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(o(i,j)-\bar{o})(T(i,j)-\bar{T})}{\sqrt{\left[\sum_{i=1}^{M}\sum_{j=1}^{N}(o(i,j)-\bar{o})^2\right]\left[\sum_{i=1}^{M}\sum_{j=1}^{N}(T(i,j)-\bar{T})^2\right]}}$$

… (17)

Where:

$o(i,j)$ is the output of neural

$\bar{o}$ is the mean of the output

$T(i,j)$ is the target

$\bar{T}$ is the mean of the target

The result of correlation between NN outputs in the testing phase with targetwithout EGR feature is 94% and when using EGR the correlation is 99%.

CONCLUSIONS

The fingerprint recognition using Gabor feature extraction with Estimation Global Region is considered in this paper and compared the result with the recognition using Gabor filter without Estimation Global Region. The proposed algorithm gives best result in fingerprint rotation with different angles**.** In this paper,the NN can recognize the feature extraction by Gabor filter for 16*16 non overlappingwindowsthat included in its data base.But changing the rotation of the fingerprint image by the angle Ѳ=5, 10, 20, the Gabor filter cannot be recognize the feature extraction. In the proposalalgorithm, the NN can recognize the feature extraction with and without the rotation. The correlation of the proposal algorithm between NN outputs in the testing phase with targetwhen using EGR is 99%. While without EGR feature, the correlation is 94%.

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| (a) | (c) | (e) | (g) | (i) |

| (b) | (d) | (f) | (h) | (i) |
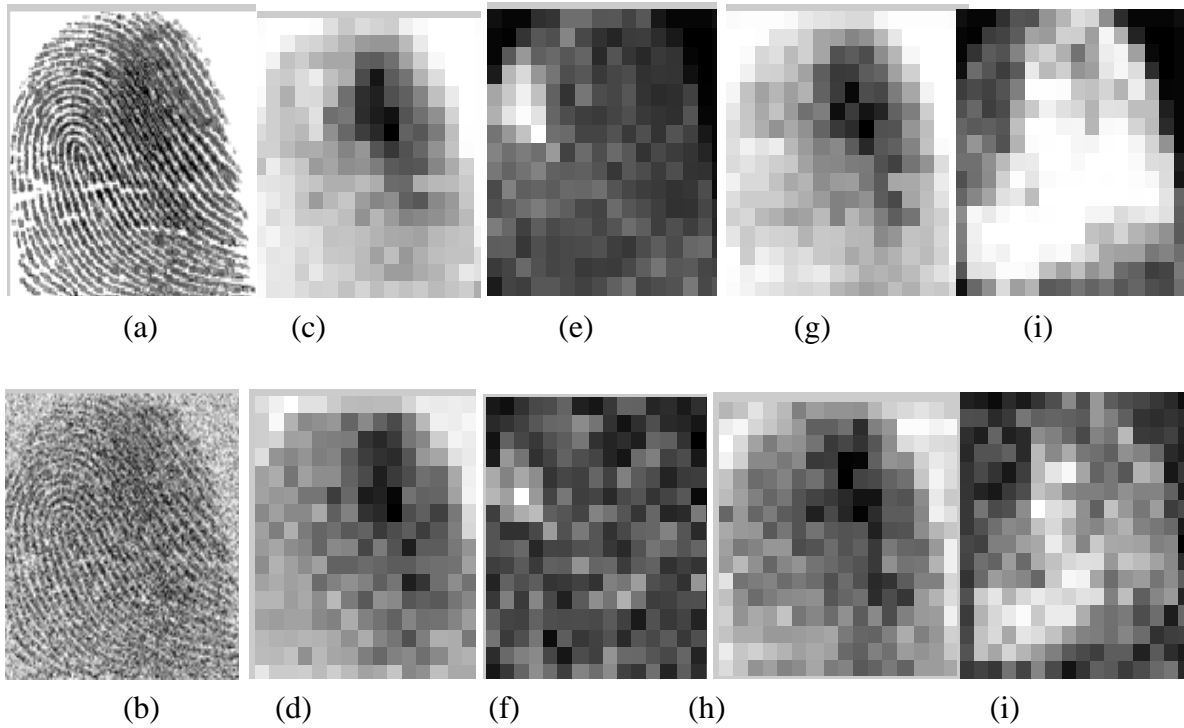
Figure(2) Magnitude Gabor features of two fingerprints belonging to the same person for (8*8 blocks)

(a) fingerprint image   (c),(d) magnitude Gabor feature with angle 0

(b) the same fingerprint image with noise   (e),(f) magnitude Gabor feature with angle 45

(g),(h) magnitude Gabor feature with angle 90   (i),(j) magnitude Gabor feature with angle 135

(a)   (c)   (e)   (g)   (i)

(b)   (d)   (f)   (h)   (J)

**Figure(3) Magnitude Gabor features of two fingerprints belonging to the same
person for (16*16 blocks)**

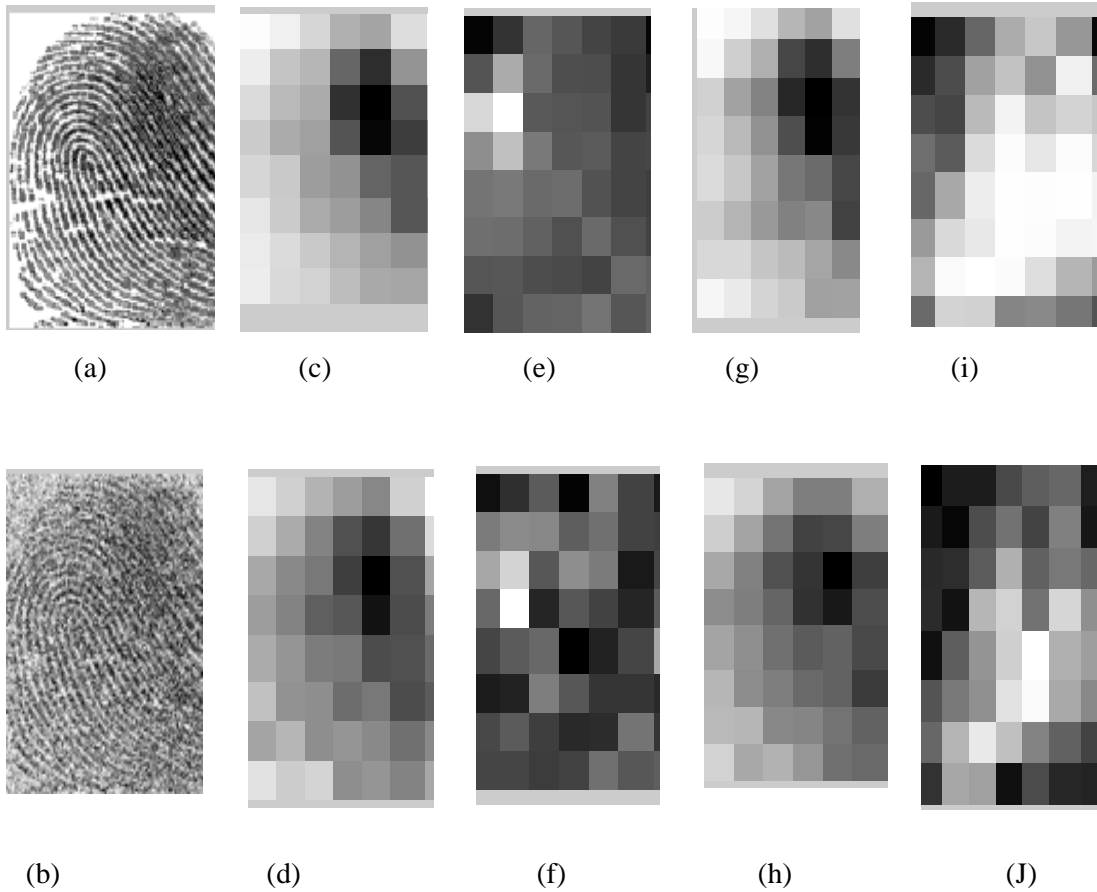(a) fingerprint image   (c),(d) magnitude Gabor
feature with angle 0

(b) the same fingerprint image with noise   (e),(f) magnitude Gabor feature
with angle 45

(g),(h) magnitude Gabor feature with angle 90   (i),(j) magnitude Gabor feature
with angle 135

(a)   (c)   (e)   (g)   (i)

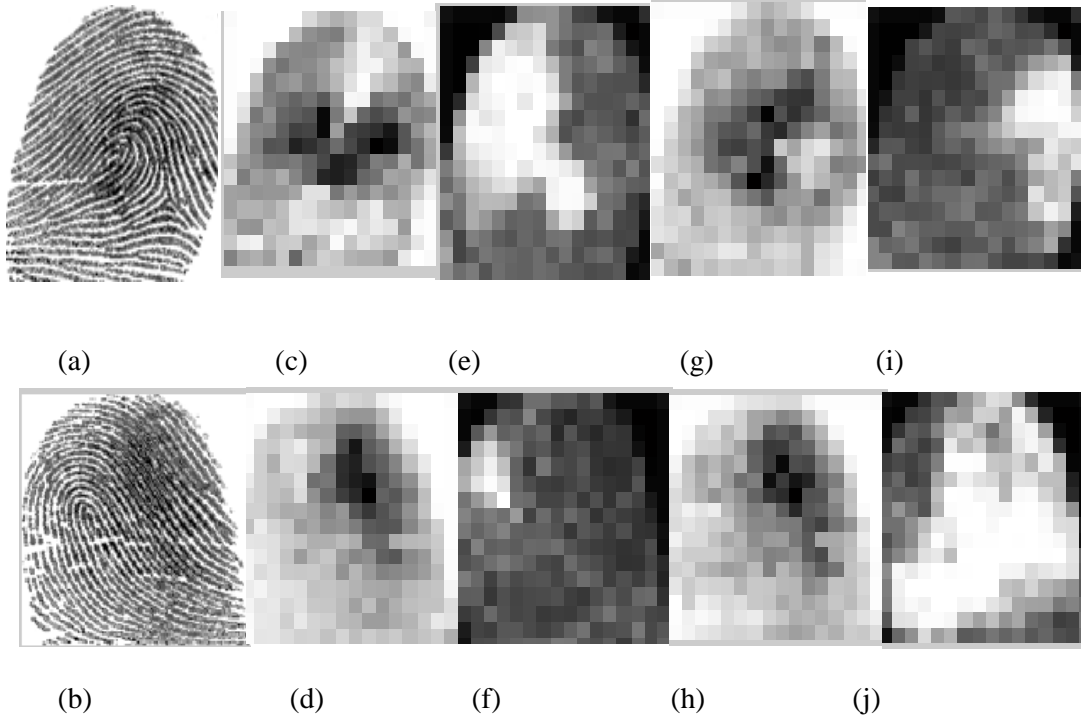(b)   (d)   (f)   (h)   (j)

Figure (4) Magnitude Gabor features of two fingerprints belonging to the different person for (8*8 blocks)

(c) fingerprint image   (c),(d) magnitude Gabor feature with angle 0

(d) another fingerprint image   (e),(f) magnitude Gabor feature with angle 45

(g),(h) magnitude Gabor feature with angle 90   (i),(j) magnitude Gabor feature with angle 135
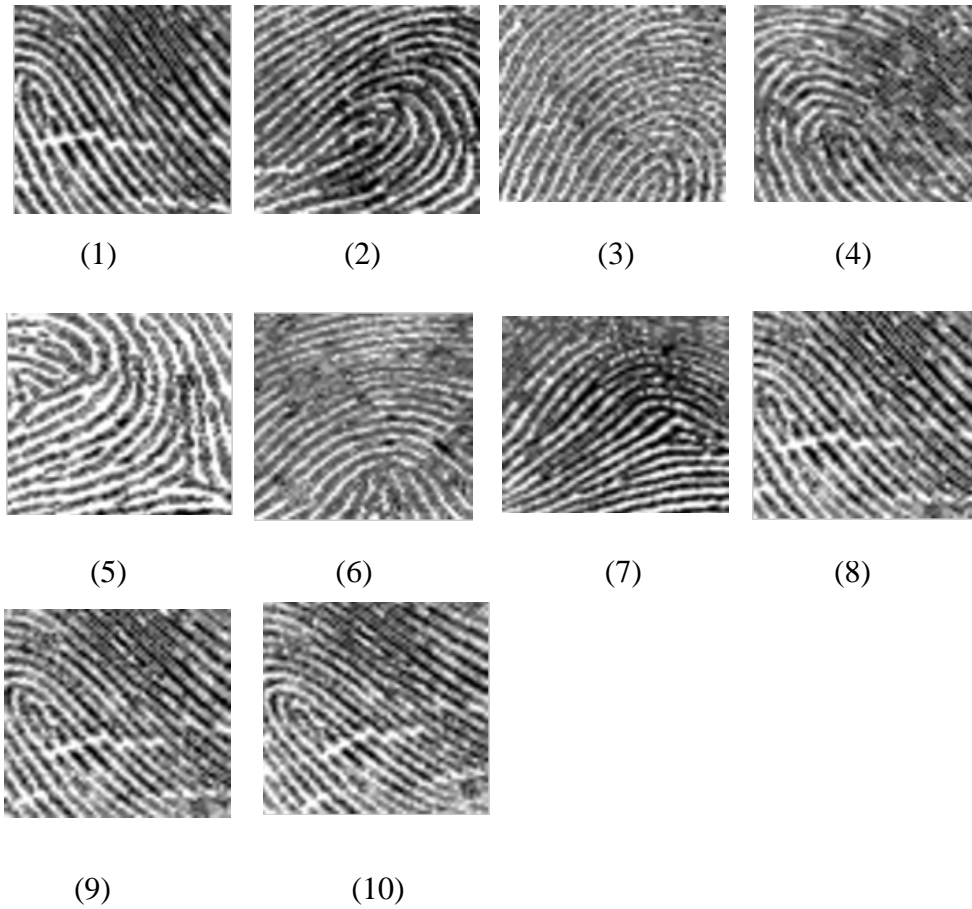
(1)   (2)   (3)   (4)

(5)   (6)   (7)   (8)

(9)   (10)

Figure (5) The Output of Estimation Global Region Algorithm
(1-7) Different fingerprint images
(8-10) The same fingerprint but with rotation angle $\theta=5^0,10^0,20^0$

Table (1) Output Of The Neural Network With Adaptive Learning Rate In The Testing Phase Without Using Estimation Global Region Algorithm

Out	P1	P2	P3	P4	P5	P6	P7	P1(5^0)	P1(10^0)	P1(20^0)
O1	**0.9827**	0.0008	0.0136	0.0097	0.0077	0.0026	0.0011	**0.5589**	**0.4851**	**0.0171**
O2	0.0084	**0.9814**	0.0096	0.0080	0.0081	0.0005	0.0063	0.0004	0.0009	0.8340
O3	0.0190	0.0131	**0.9713**	0.0071	0.0050	0.0066	0.0104	0.0000	0.0000	0.0001
O4	0.0083	0.0095	0.0018	**0.9848**	0.0010	0.0014	0.0015	0.0011	0.0001	0.0003
O5	0.0095	0.0084	0.0008	0.0023	**0.9819**	0.0080	0.0060	0.0023	0.0009	0.0002
O6	0.0094	0.0005	0.0072	0.0041	0.0093	**0.9906**	0.0035	0.0058	0.0001	0.0001
O7	0.0017	0.0122	0.0140	0.0028	0.0038	0.0036	**0.9863**	0.0010	0.0016	0.0126

Table (2) Output Of The Neural Network With Adaptive Learning Rate In The Testing Phase With Using Estimation Global Region Algorithm

| Out	P1	P2	P3	P4	P5	P6	P7	P1(5^0)	P1(10^0)	P1(20^0)
O1	**0.9820**	0.0096	0.0091	0.0129	0.0063	0.0077	0.0060	**0.9786**	**0.9298**	**0.5000**
O2	0.0089	**0.9875**	0.0044	0.0091	0.0123	0.0011	0.0011	0.0006	0.0009	0.0009
O3	0.0137	0.0034	**0.9886**	0.0042	0.0070	0.0095	0.0095	0.0000	0.0000	0.0000
O4	0.0131	0.0072	0.0030	**0.9794**	0.0110	0.0092	0.0075	0.0036	0.0076	0.0007
O5	0.0059	0.0096	0.0005	0.0147	**0.9826**	0.0022	0.0138	0.0026	0.0084	0.0016
O6	0.0073	0.0044	0.0057	0.0121	0.0038	**0.9861**	0.0125	0.0009	0.0070	0.0105
O7	0.0009	0.0109	0.0037	0.0037	0.0038	0.0058	**0.9863**	0.0010	0.0020	0.0070
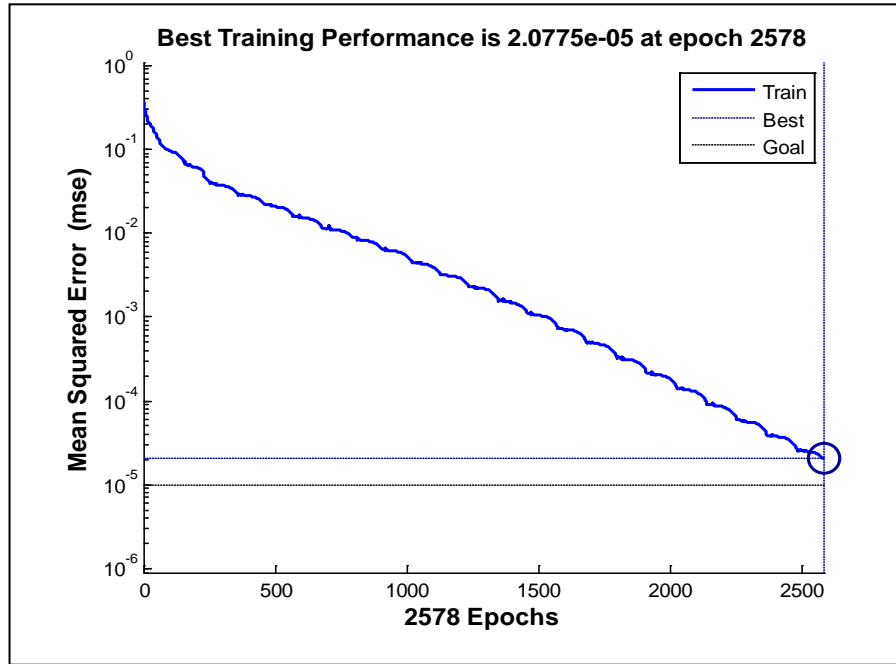
Figure (6) Epochs of NN in learning phase
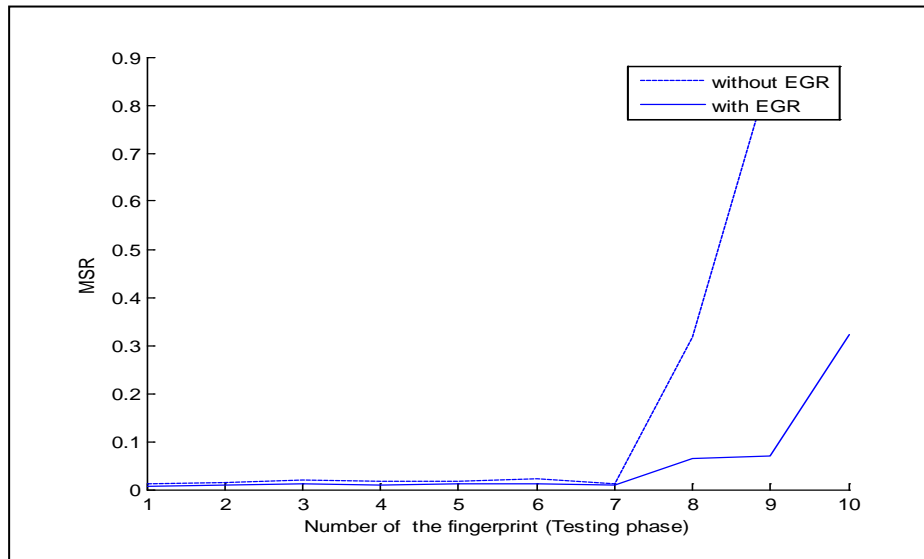
Figure (7) Mean square error between output to NN and target.