Classification and Recognition of Fingerprints using Self Organizing Maps(SOM)

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Abstract

Feature extraction and matching are important in automatic fingerprint identification systems(AFIS) in the field of biometric technology. In this work, a filter-based algorithm uses a bank of Gabor filters to capture local and global features in a fingerprint as a compact fixed length FingerCode. These fingercodes are matched using Self Organizing Maps (SOM). Promising results of classification of fingerprints in research works using neural network has pushed us to exploit another version of neural networks, SOM and to develop codes and recognition algorithms which are associated to this system. Our Experimental results demonstrate the robustness of our algorithm in terms of Total Acceptance Rate (TSR), False Rejection Rate (FRR) and False Acceptance Rate(FAR).

Keywords: *Fingerprints, Biometrics, Fingercodes, Gabor Filters, Self Organising Maps (SOM).*

1. Introduction

Biometrics, the ability to identify an individual based on his or her physiological, behavioral, chemical and biological characteristics, has the potential to reliably distinguish between an authorized person and an imposter.

Biometrics is used in two major ways: Identification and Verification.

Identification is determining who a person is. It involves taking the measured characteristic and trying to find a match in a database containing records of people and that characteristic.

Verification is determining if a person is who they say they are. It involves taking the measured characteristic and comparing it to the previously recorded data for that person.

Biometrics can be divided into three branches namely physiological (e.g. face, fingerprint, hand, iris), Behavioral (e.g. keystroke, gait, signature, voice), and Chemical and Biological (eg. DNA, blood glucose, skin Spectrograph).

Among all the biometrics, fingerprint-based identification is one of the most mature and well known technique because fingerprint contains the following significant characteristics:

- Acceptability: this is the degree of approval of a technology.
- Uniqueness: is how well the biometric separates individually from another.
- Collectability: ease of acquisition for measurement.
- Permanence: measures how well a biometric resists aging.
- Performance: accuracy, speed, and robustness of technology used.

- Circumvention: ease of use of a substitute.

The finger tip surface is covered by a pattern of ridges and valleys. These ridges and valleys contain information (minutiae) that is very important in fingerprint recognition. According to Rao and Jain (1992), the pattern of ridges and valleys in a fingerprint can be viewed as an oriented texture field, whose height and direction vary continously.Therefore points on a fingerprint image have a dominant local orientation and a local measure of coherence from their flow pattern. The uniqueness of a fingerprint is exclusively determined by the local ridge characteristics and their relationships, Hong et al (1998). These unique characteristics heavily depend on the quality of the impression conditions and quality of the fingerprint image.

Anomalies in ridge flow pattern are characterized as Minutiae points which consists of ridge ending; the point at which a ridge terminates and Bifurcations; the points at which a single ridge splits into two ridges. Some researchers classify fingerprints by using algorithms to detect the presence of Singular Points (SP) which are the cores and deltas on the fingerprint surface, Kalle karu and Anil K.Jain (1996).

A core point is the topmost point of the innermost curving ridge and a delta point is the center of triangular regions López et al (2012). Our interest is in the accurate detection of core point in every fingerprint so as to achieve a good performance accuracy from our system.

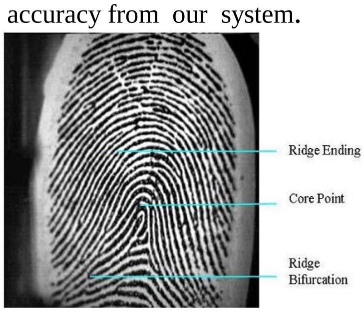

Fig. 1 Source Elmir et al, 2007

At the highest level, all Fingerprint recognition systems contain these modules:

- Image acquisition,
- Image Preprocessing
- Feature extraction
- Feature Matching.

Image acquisition is a process that accepts real images as digital images, typically from a physical scene through a device e.g. a sensor to process, compress, store, print, and display the image. The acquired fingerprint is then stored in a database, along with some identification such as username or any other uniquely assigned code.

Image preprocessing involves the use of algorithms to reduce noise and any corruptions in the fingerprint image so that accurate results can be achieved, mostly by ridge enhancements, binarisation, thinning etc.

Feature extraction is the process that detects singular and all other minutiae points which are ridge ending and ridge bifurcation which differentiate one fingerprint from another.

Feature matching in this study is performed through SOM using fingercodes presented by two fingerprints.

1.1 Problem Statement

A Self Organisng Map (SOM) is to be trained to recognize the fingercodes on a database. An imaging system that converts each minutiae image obtained from a fingerprint image to fingercode or minutiae matrix code by using a bank of Gabor filters is to be employed.

The result is that each fingerprint image is represented as a vector. These fingercodes are then stored on a database. Matching based on euclidean distance through SOM is performed and the system is tested through FAR (False Acceptance Ratio) and FRR (False Rejection Ratio) to determine the performance and robustness of our system. Finally, results obtained by SOM neural network will be compared to other previous works by other researchers.

This study seeks to examine how biometric fingerprint-based identifications perform on Self Organizing Maps(SOMs).

2. Methodology

To ensure that the performance of feature extraction and reference point location algorithm is accurate, we adopt a Multiple Resolution Analysis approach based on Jain et al (2000) which locates a reference point (core point) on a given fingerprint image by gracefully handling the local noise on the image. This method considers a large neighborhood in the fingerprint and has the following steps:

i. A fingerprint image I is divided into a set of $w \times w$ non overlapping blocks and a single orientation is defined for each block.

ii. The gradients $\partial_x(i, j)$ and $\partial_y(i, j)$ are computed for each pixel $(i,,j)$.

iii. The average gradient direction $O(i, j)$ at each block centered at each pixel (i, j) is estimated as follows :

$$V_x(i,j)=\sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}}\sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2\partial_x(u,v)\partial_y(u,v) \qquad (1)$$

$$V_y(i,j)=\sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}}\sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} (\partial_x^2(u,v)\partial_y^2\ (u,v)) \qquad (2)$$

$$\mathrm{O}(i,j)=\frac{1}{2}\tan^{-1}\left(\frac{V_x(i,j)}{V_y(i,j)}\right) \qquad (3)$$

Local ridge orientation is usually specified for a block rather than at every pixel;

$\mathrm{O}(i,j)$, is the least square estimate of the local ridge orientation of the block centered at pixel (i, j).

Orientation of a local ridge may not always be correct because of the presence of noise. We smooth the orientation field in the local neighbourhood. To enable us to perform smoothing (low pass filtering), the orientation image is converted into a continuous vector field through the following. A unit integral filter with size $w_\Phi \times w_\Phi$ is adopted to smooth the orientation field:

$$\Phi_x(i,j)=\cos(2\mathrm{O}\ (i,j)), \qquad (4)$$

$$\Phi_y(i,j)=\sin(2\mathrm{O}(i,j)), \qquad (5)$$

Where Φ_x and Φ_y are the *x* and *y* components of the vector field, respectively. A low-pass filter below is applied to the continuous vector field.

$$\Phi'_x(i,j)=\sum_{u=-\frac{w_\Phi}{2}}^{\frac{w_\Phi}{2}}\sum_{v=-\frac{w_\Phi}{2}}^{\frac{w_\Phi}{2}} W(u,v).\Phi_x(i-uw,j-vw) \qquad (6)$$

$$\Phi'_y(i,j)=\sum_{u=-\frac{w_\Phi}{2}}^{\frac{w_\Phi}{2}}\sum_{v=-\frac{w_\Phi}{2}}^{\frac{w_\Phi}{2}} W(u,v).\Phi_y(i-uw,j-vw) \qquad (7)$$

W is a two-dimensional low-pass filter with unit integral.

The smoothed orientation field of the fingerprint image at each pixel (*i*, *j*) is computed using:

$$\mathrm{O}'(i,j)=\frac{1}{2}\tan^{-1}\left(\frac{\Phi'_y(i,j)}{\Phi'_x(i,j)}\right) \qquad (8)$$

We compute ε , an image containing only the *sine* component of O'.

$$\varepsilon(i,j)=\sin(\mathrm{O}'(i,j)) \qquad (9)$$

iv) Initialize A , a label image used to indicate the reference point.

v) For every pixel (i,j) in ε , we integrate pixel intensities and assign the corresponding pixels in A the value of their difference

$$A(i,j)=\sum_{R_1}\varepsilon(i,j)-\sum_{R_{II}}\varepsilon(i,j) \qquad (10)$$

where R_I and R_{II} are Regions for integrating E pixel intensities for A(i; j).

vi) We find the maximum value and assign its coordinate to the core, i.e., the reference point

vii) For a fixed number of times, we repeat steps (i) – (vi) by using a window size of $w' \times w'$, where $w' \prec w$ and restrict the search for the reference point in step (vi) in a local neighborhood of the detected reference point.

2.1 Tessellation of the Region of Interest

Our region of interest is defined as the collection of all the sectors S_i , where the ith sector S_i is computed in terms of parameters (r,θ) as follows:

$$S_i=\left\{(x,y)\middle| b(T_i+2),\theta_i\le\theta\prec\theta_{i+1},1\le x\le N,1\le y\le M\right\} \qquad (11)$$

where,

$$T_i = idivk \qquad (12)$$

$$\theta_i=(i \bmod k)\times(\frac{2\pi}{k}) \qquad (13)$$

$$r=\sqrt{(x-x_c)^2+}(y-y_c)^2 \qquad (14)$$

$$\theta=\tan^{-1}(\frac{(y-y_c)}{(x-x_c)}) \qquad (15)$$

b is the width of each band, k is the number of sectors considered in each band, $i=0...(B\times k-1)$, where B is the number of concentric bands considered around the reference point for feature extraction. These parameters depend on the image size and resolution. Before we filter the fingerprint image, we normalize the region of interest in each sector separately to a constant mean and variance.

Let $I(x,y)$ denote the gray value at pixel (x,y), M_i and V_i , the estimated mean and variance of sector s_i , respectively, and $N_i(x,y)$, the normalized gray-level value at pixel (x,y), For all the pixels in sector s_i , the normalized image is given by:

$$N_i(x,y)=\left\{\begin{array}{l} M_o+\sqrt{\dfrac{V_0\times(I(x,y)-M_i)^2)}{V_i}}, if I(x,y)\succ M_i \\ M_o-\sqrt{\dfrac{V_0\times(I(x,y)-M_i)^2)}{V_i}} \end{array}\right\} \quad (16)$$

M_O and V_o are the desired mean and variance values respectively.

A properly tuned Gabor filters is used to remove noise, preserve information contained in a particular orientation in the image Jain et al (2000).

$$G(x,y:f,\theta)=\exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\partial_{x'}^2}+\frac{y'^2}{\partial_{y'}^2}\right]\right\}\cos(2\pi fx') \quad (17)$$

$$x' = x\sin\theta + y\cos\theta \quad (18)$$

$$y' = x\cos\theta - y\sin\theta \quad (19)$$

where f is the frequency of the sinusoidal plane wave along the direction from the x -axis, $\partial_{x'}$ and $\partial_{y'}$ and are the space constants of the Gaussian envelope along x' and y' axes, respectively.

$\theta = 0^0, 22.5^0, 45^0, 67.5^0, 90^0, 112.5^0, 135^0 157.5^0$ with respect to the x-axis.

Let $F_{i\theta}(x,y)$ be the θ -direction filtered image for a sector. Now, $\forall i \in \{0,1,.....,79\}$ and $\theta \in \{0^0, 22.5^0, 45^0, 67^0, 90^0, 112.5^0, 135^0, 157.5^0\}$, the feature value, $V_{i\theta}$, is the average absolute deviation from the mean defined as

$$V_{i\theta} = \frac{1}{n_i}\left(\sum_{n_i}\left|F_{i\theta}(x,y)-P_{i\theta}\right|\right) \quad (20)$$

where n_i is the number of pixels in S_i and $P_{i\theta}$ is the mean of pixel values of $F_{i\theta}(x,y)$ in sector S_i . The average absolute deviation of each sector in each of the eight filtered images defines the components of our feature vector.

Feature values are collected based on two different rotations, The feature value is composed of an ordered enumeration of the features extracted from the (local) information contained in each sub image (sector) specified by the tessellation.

Fingerprint Verification Competition (FVC) 2004 database consisting of 110 fingers with eight impressions per finger totaling 880 fingerprints is used for this work. Our experiment is run on MATLAB R2012a with windows application running on 64-bit operating system having the following specifications:

- Intel(R) Core (Tm) i5-3210M CPU (Processor)
- 6 GB of RAM (Memory)
- 750 GB (Hard Disk)
- Windows 7 Home Premium installed as the Operating System (OS). SOM downloaded free from http://www.cis.hut.fi/projects/somtoolbox

3. RESULTS

The results of the fingercodes from the method described above are stored on a database data880.data.

An automatic method for classifying minutiae correspondences in the 110 images are applied based on the theory of the SOMs. The fingercodes are read and normalized to fall in the range [0, 1] from the database. This is done to ensure that none of the data has overwhelming influence on the training result.

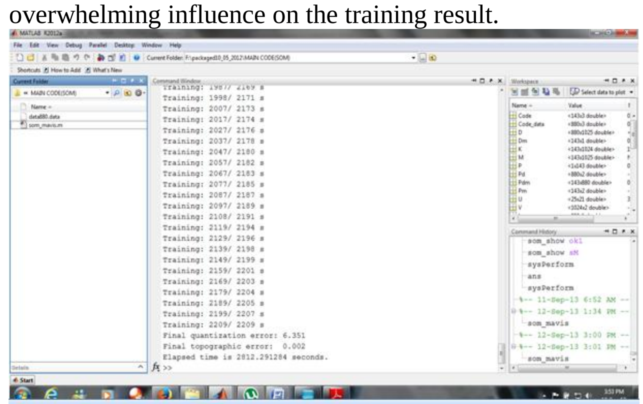

Fig. 2 Training Data880.data

The U-matrix (unified distance matrix) a representation of SOM where the Euclidean distance between the codebook vectors of neighboring neurons is depicted in a grayscale image is used to visualize the data in a high-dimensional space using a 2D image.

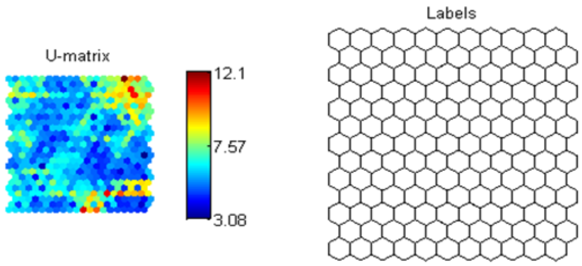

Fig. 3 Results of trained fingercodes in U-matrix

This representation has helped to visualize the clusters of the fingercodes in the high-dimensional space. We automatically label our data map to enhance our classification process .

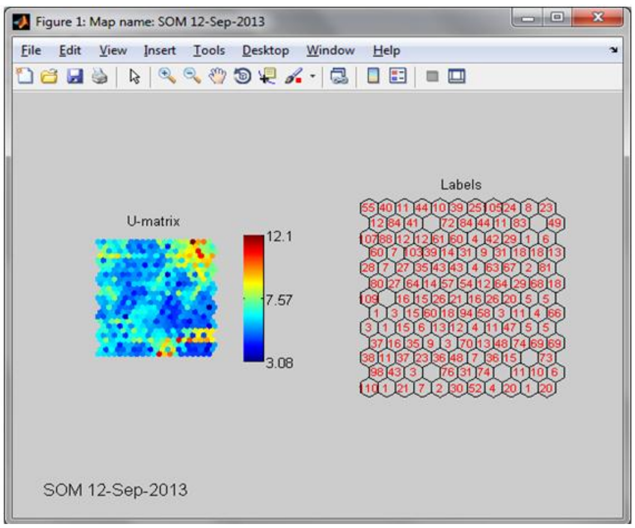

Fig.4 Labelled Fingercodes

We use the SOM show to display how the data looks like on a map after vector projection algorithm, a SOM function has been applied.

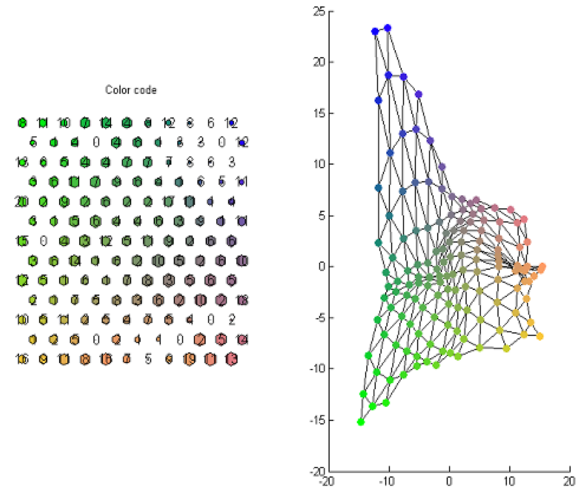

Fig.5 K-Means Cluster

We performed K- means clustering based on eight clusters in accordance to the number of fingerprints per individual through a mathlab function .

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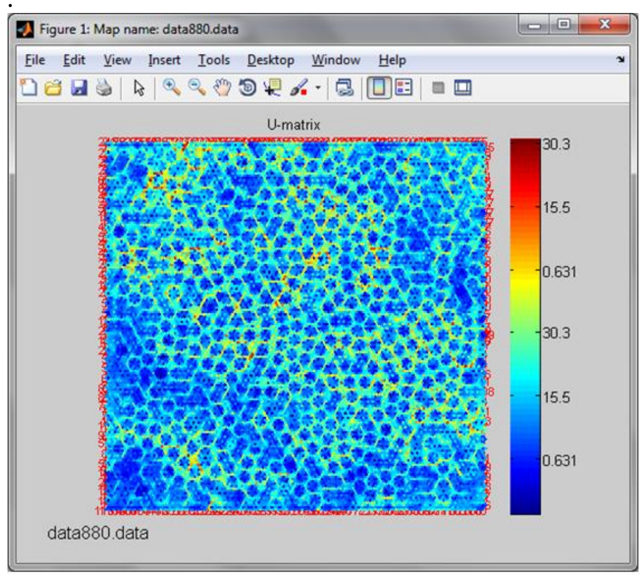

Fig.6 Results of denormalization.

and this resulted in "SOM Training and Classification terminated Successfully with Error Rate of 1.7045%" as shown in Fig 7.

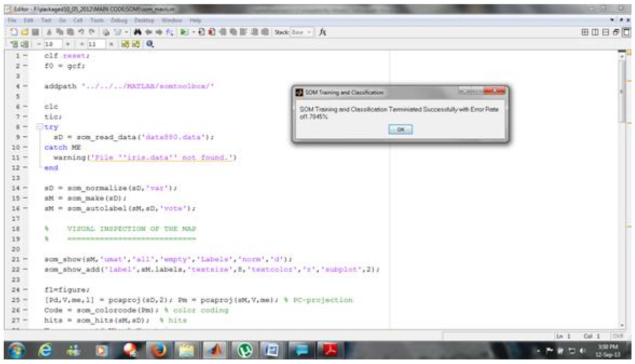

Fig. 7 Results of SOM classification

This result pushed us to exploit SOM for biometric recognition Testing, using the FAR (false Acceptance Ratio) and FRR (False Rejection Ratio) performance ratios.

FAR is the fraction of times the system incorrectly identifies two fingercodes representing the same finger.
FAR is given by:

$$FAR = \frac{\text{number of falsely accepted images}}{\text{Total number of persons out of the database}}$$

A database FAR.data was created by taking the last 80 generated fingercodes from the 880 fingerprints in data880.data.

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FRR (False Rejection Ratio) is given by :

$$FRR = \frac{\text{number of falsely rejected images}}{\text{Total number of persons in the database}}$$

FRR.data is created by taking 100 fingercodes out of data880.data.. These are the fingercodes of the eighth fingerprint image of each individual.
The remaining 700 fingercodes are stored in a different file data880Attempt.data.The data in FAR.data is untrained and the 700 fingercodes are trained on SOM. Matches between the FAR.data and data880Attempt.data generated 0% error. However matches between the FRR.data and data880Attempt.data generated an 18% error.

This means we have achieved a Total success Rate of 82%.The FAR was implemented by testing FAR.data against data880.com collected. The FRR was implemented by collecting the eighth fingercode of each individual numbering 100 fingercodes against the remaining 700 fingercodes.

In ideal case FAR and FRR should be zero. In practice this is not so because a given biometric application will dictate the FAR and FRR requirements. For instance access to ATM needs a small FRR whilst military installation requires a very small FAR. The overall total success rate of 82 % is acceptable when compared to the performances achieved by other researchers in the biometric field as shown in fig 8.

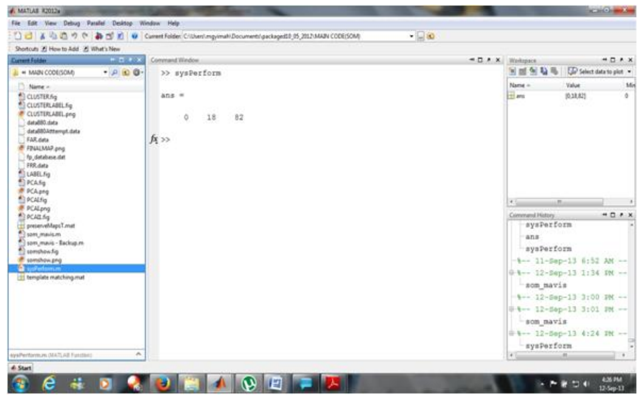

Fig. 8 Results of FAR, FRR,TSR

3.1 COMPARISON OF WORK:

We compare our work by looking at other research works with the results obtained. Elmir et al, 2007 "Personal Identification by Fingerprints based on Gabor Filters" using Spike Neural Network achieved 73.68% recognition rate on FVC2004 DB3 A.
Other research works we looked at were performed using different database , but we observed their recognition rates. Zhou et al, 2004 on FVC 2000, "Singular Points Analysis in Fingerprints Based on Topological Structure and Orientation Field". The percentages for correct, missing, and false detection are :

	Correct	Missing	False Detection
Percentage	80.6%	14.6%	4.8%

Table 1 The performance of the proposed algorithm Source:

4. Conclusion

We have demonstrated the power of computational neuroscience in areas as diverse as artificial intelligence. We have achieved an identification accuracy with a performance level of TSR of 82% which is comparable to results obtained by other methods on minutiae-based fingerprint. The prime advantage of our method is with decreasing time cost of matching saliently. However, because reference point cannot be accurately located in a noisy image and since the generation of fingercodes significantly depends on the quality of fingerprint minutiae, there is still the need to do more research in feature extraction techniques of fingerprints in the near future.

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