Proceedings of the 2nd ICEENG Conference, 23-25 Nov. 1999

SP-8	1

Military Technical College
Kobry Elkobbah,
Cairo, Egypt

ICEENG 99

2nd International Conference
on Electrical Engineering
ICEENG 99

AN IMPROVED FINGERPRINT CLASSIFICATION TECHNIQUE

Wafaa M. Shalash* and Fatma Abou-Chadi**

ABSTRACT

This paper presents an automatic fingerprint classification technique similar to that reported in [2] but, an inverse filtering technique was introduced to restore the distorted parts of the images prior to the feature extraction stage. The results have shown that introducing the inverse filter stage has improved the percentage of correct classification. It reaches 97.5% compared to the 95% correct classification obtained using the previously reported technique.

KEY WORDS

Fingerprint classification, Image processing, Neural networks classifiers, Biometrics.

*Scholarship student, Dept. of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, Egypt, (e-mail: wshalash@mum.mans.eun.eg).
**Professor, Dept. of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, Egypt, (e-mail: f-abochadi@ieee.org).

I. INTRODUCTION

Fingerprints have been used for personal identification for a long time. Each fingerprint is a map of ridges and valleys in the epidermis layer of the skin, which forms unique geometric patterns. The ridge endings and bifurcation are called minutiae and these minutiae have a unique and permanent pattern for each person even twins [8].

Henry [9] examined the global structure of fingerprints and devised a classification method for partitioning the large fingerprint database into five basic classes. These five classes are right loop, left loop, whorl, arch and tented arch. Examples of these classes are shown in Figure 1. Even today, most identification applications perform initial partitioning according to Henry classification prior to obtain an exact matching.

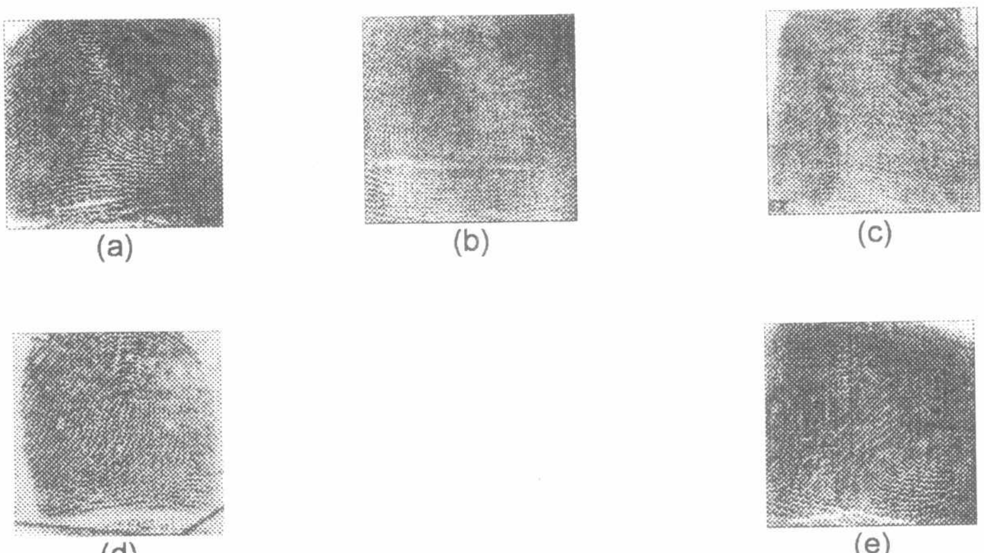


Fig.1. The five basic classes of fingerprint: a) Arch, b) Whorl, c) Tented arch, d) Left loop and e) Right loop.

In accordance with the U.S Federal Bureau of Investigation (FBI) representation of fingerprints ridge endings and bifurcation (Figure 2) are taken as the distinctive feature of the fingerprints, whereas the coordinates and the angle of the features are used to represent the fingerprint in the matching process. In addition to these minutiae, fingerprints contain two special kinds of feature called core and delta points (Figure 3). These points are often referenced to as singularity points of fingerprint. The core point is generally used as a reference point for coding minutiae and is defined as topmost point on the inner most recurving ridge [10].

In many cases there is a need to identify a person through his fingerprint, a clear example of this case arises in police agencies when it has to identify a person through a latent fingerprint found on a crime scene.


(a) (b)

Fig.2. a) Ridge ending. b) Ridge bifurcation.

Fig.3. Singularity points on a fingerprint.

As the size of fingerprint databases increase, it becomes very difficult or impossible to do classification manually and the use of an automatic fingerprint identification system (AFIS) becomes necessary. Most AFIS today have the basic structure shown in Figure 4. Recently, Halaci and Ongun [2] have reported a fingerprint classification using a self-organizing feature map (SOFM). However, it has been found that the proposed system reaches 95% recognition. This is due to the fact that fingerprint images may have distorted regions. In this paper, a pre-processing stage (section II) has been adopted to enhance the image prior to the feature extraction stage (section III and IV). The effect on the performance of the classifier was studied (section V) and the results were compared with those obtained from the SOFM classifier without pre-processing (section VI).

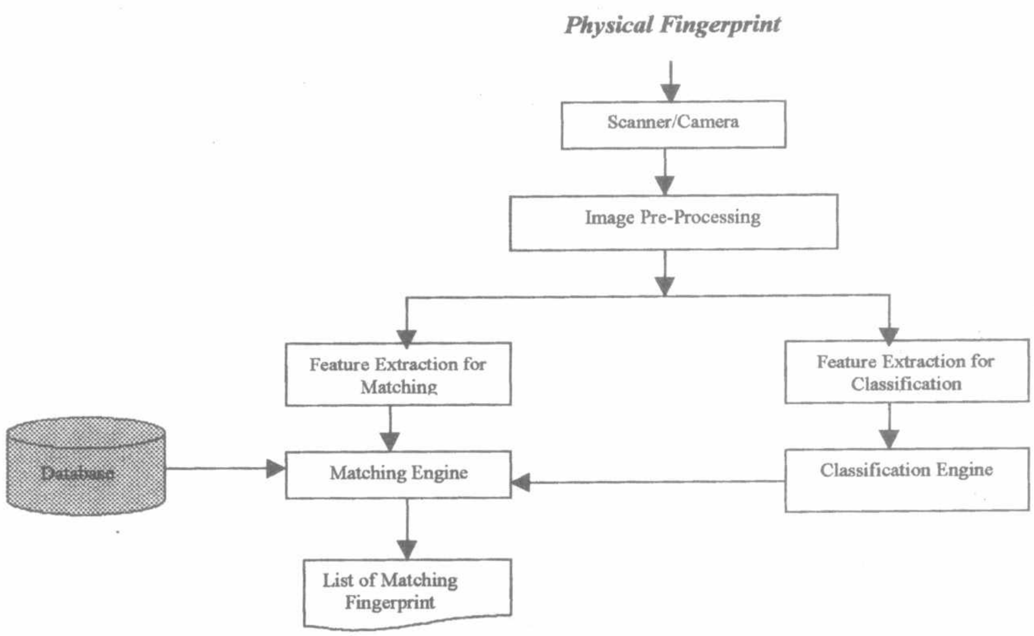


Fig.4. Block diagram of basic AFIS components.

II. FINGERPRINT IMAGE PRE-PROCESSING (INVERSE FILTERING)

Assume that the degraded picture is $g(x,y)$ and the original picture is $f(x,y)$ then, the Fourier transforms (if exist) of $g(x,y)$, $f(x,y)$, and the PSF (point spread function of degradation) $h(x,y)$ satisfy

$$G(u,v) = H(u,v)\, F(u,v) \qquad (1)$$

or equivalently,

$$F(u,v)=G(u,v)/H(u,v) \qquad (2)$$

This implies that if $H(u,v)$ is known, we can restore $F(x,y)$ by multiplying the Fourier transform $G(x,y)$ of the degraded image by $1/H(u,v)$ and then inversing Fourier transforms. In other words, the filter transfer function is

$$M(u,v) = 1/H(u,v) \qquad (3)$$

There is considerable arbitrariness in the selection of M(u,v), a rectangular scanning aperture was chosen as in [4]

$$h(x,y) = rect(\frac{x}{\alpha}, \frac{y}{\beta}) \qquad (4)$$

or,

$$H(u,v) = \alpha\beta \,\mathrm{Sinc}(\alpha u)\ \mathrm{Sinc}(\beta v) \qquad (5)$$

where, α, β are chosen constants.

In many cases the magnitude of $H(u,v)$ drops rapidly with distance from the origin in the uv-plane. To avoid very high or infinite values Eq.(3) can be rewritten as:

$$M(u,v) = \begin{cases} 1/H(u,v) & if\, H(u,v) \geq Threshold \\ 1/Threshold & if\, H(u,v) < Threshold \end{cases} \qquad (6)$$

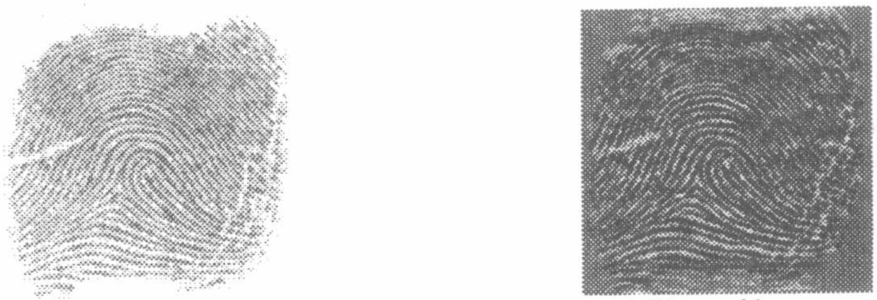
where, *Threshold* is a chosen threshold.

One way to avoid arbitrariness in inverse filter is to find a restoration $\hat{f}(x,y)$ of the picture $f(x,y)$ minimizing some difference between $\hat{f}(x,y)$ and $f(x,y)$. This can be done by applying least square filtering [3], which minimizes the least square error between the original picture and the degraded one. This is attained by using [3], [4] :

$$M(u,v) = \frac{1}{H(u,v)} \frac{|H(u,v)|^2}{|H(u,v)|^2 + \Gamma} \qquad (7)$$

Where Γ the noise to signal power density ratio and it is approximated by a suitable constant. The value of this constant evidently reflects some a prior knowledge about the relative magnitudes of signal and noise power in the picture.

Figure 5 shows the results obtained from the application of least square filter to a fingerprint image.



a) Original image. b) Filtered image.

Fig. 5. Inverse filter output.

III. FEATURE VECTOR GENERATION FOR CLASSIFICATION

This step is a very important step when neural networks are used for classification. The block directional image as a feature vector was chosen in [1] and a comparison between three methods used in block directional feature vector generation was reported. The three methods are the Fast Fourier Transform (FFT), Gabor filter and ridge-valley filter. It was found that FFT and Gabor features take longer computation time and produce inferior results than the ridge-valley filter method so, the ridge-valley filter method was chosen.

Ridge-Valley Filter

The mask shown in Figure 6 was applied to each pixel on the image. There are eight slits on the mask, each of which is shown in figure with different slit numbers assigned to grids. A slit sum s_i for i =1,2,...,8 is defined as the summation of the intensity values of the pixels having the same slit number i while S is the intensity value of center point C. After computing these parameters, the pixel C is assigned a direction according to the following:

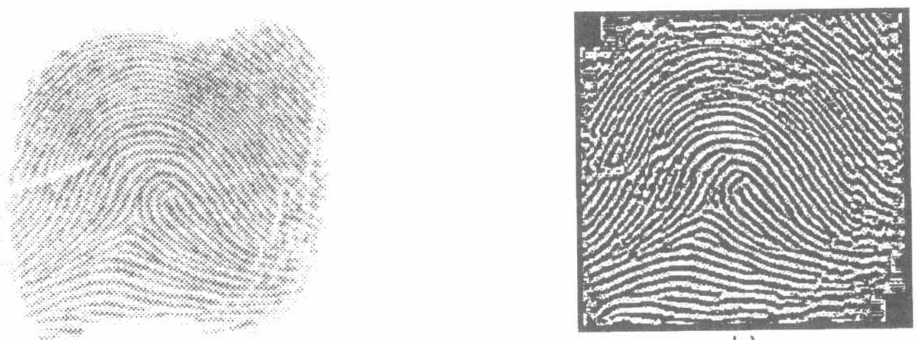
$$direction(C) = \begin{cases} \text{direction}(s_{\max}) & \text{if } 4S + s_{\max} + s_{\min} > \dfrac{3}{8}\sum_{i=1}^{8} s_i \\ \text{direction}(s_{\min}) & \text{otherwise} \end{cases} \tag{8}$$

A direction image is obtained by moving the mask and applying the algorithm. Thus every image pixel has a direction quantized to one of the eight angles, which varies from zero to 180° with 22.5° steps.

7		8		1		2		3
6		7	8	1	2	3		4
		6				4		
5		5		C		5		5
		4				6		
4		3	2	1	8	7		6
3		2		1		8		7

Fig.6. Ridge-Valley filtering mask.

This process produces 256 $\times$ 256 element as the input image. To obtain much smaller grid of directions, spaced every 16 pixel, the pixel directions are averaged over 16 $\times$16 pixel squares. Averaging has a smoothing effect and produces a finer quantization of directions. The averaging process doesn't produced by summing pixels direction over each grid and divide the sum by 16$\times$ 16, instead as we have ridge angel θ and pixel direction vector $(\cos 2\theta, \sin 2\theta)$ then, this vector direction is averaged over each grid. Figure 7 shows an example of ridge-valley filter.
The last remaining step is to do core point extraction to find the singularity point and align the resulting directional feature vector according it. An algorithm that uses block directional map to find the core by comparing the slopes of block directions is provided in [1],[2].



a) b)
Fig. 7. Ridge-Valley filter output a) The original input image, b) After the ridge valley filter.

IV. KARHUNEN-LOEVE TRANSFORM

The raw fingerprint image is assumed to contain 256$\times$256 8-bit pixel of data. After directional image and feature vector generation (section III) this number reduced to 16$\times$16 feature. This number is still high for classification because, as discussed in [5] there are many problems which arises in attempt to perform pattern recognition in high dimensional spaces and there is a potential improvements which can be achieved by first mapping the data into a space of lower dimensionality. The procedures we shall discuss in this section rely entirely on the input data itself without reference to the corresponding target data, and can be regarded as a form of unsupervised learning.
The Karhunen-Loeve (K-L) transform finds the representation of the input vector in terms of the eigenvectors of their covariance matrix. It has an excellent energy compaction property, therefore it is frequently used in statistical pattern recognition [5].
Given an ensemble of *M* real valued vectors, $x^k \in R^n, 1 \le k \le M$, their covariance R_x matrix is calculated as:

$$R_x = \frac{1}{M}\sum_{k=1}^{M}(x^k - \hat{x})(x^k - \hat{x})^T \qquad (9)$$

where,

$$\hat{x} = \frac{1}{M}\sum_{k=1}^{M} x^k \qquad (10)$$

The unit length eigenvectors of R_x are the orthogonal basis for K-L transform and are obtained by solving the following equation:

$$R_x \psi = \psi \Lambda \qquad (11)$$

where, Λ is a diagonal matrix having the eigenvalues of R_x and ψ is the modal matrix having eigenvectors of R_x for its columns, ordered in decreasing eigenvalues. After determining ψ, the K-L transform of any vector can found as

$$v = \psi^T x \qquad (12)$$

Reducing ψ to ψ^m by eliminating the last (n-m) eigenvectors results in an m-dimensional subspace spanned by the remaining m eigenvectors in ψ^m. These eigenvectors are called the principal components and the subspace spanned by them is called the principal subspace. It results in dimensionality reduction if ψ^m is used instead of ψ in Eq. (12). If the *mth* eigenvalue is considerably small when compared to the first eigenvalues, the vector transformed to the principal subspace carry approximately the same information as the original vector even though the dimensionality is reduced.

V. FINGERPRINTS CLASSIFICATION USING (SOM) NEURAL NET

The SOM is a special neural network that accepts *n*-dimensional input vectors and maps them to a lower dimensional, usually 2-D, output plane. The topology for a typical SOM network is shown in Figure 8. It has *n* input nodes and *m* by *m* output nodes. Each output node *j* in the SOM network has a connection from each input node *i*, where w_{ij} being the connection weight between them [7], [11], [12].

There are two phases of operation in SOM: the training phase and the classification phase. Classification is fairly simple after the training phase has been completed successfully. The network finds an output node such that the Euclidean distance between the current input vector and the weight set connecting the input nodes to this output node is the minimum. This node is called the winner and weights of the neighboring output nodes of the winner are updated so that the new weight set is closer to the current input vector. This procedure is applied repeatedly for all input vectors until weights are stabilized. The choice of the neighborhood function, the learning rate and the termination criteria are all problem dependent.

The training steps of the original SOM are as follows:

1) assign small random values to weights w_{ij} ;

2) chose a vector ***x*** from the sample space and apply it as input;

3) find the winning output node d_{win} by the following criterion:

$$d_{win} = \min_j \{\sum_{i=0}^{n-1} (x_i(t) - w_{ij}(t))^2\} \qquad (13)$$

where $w_{ij}(t)$ is the weight from input node *i* to the output node *j* at time t;

4) adjust the weight vectors according to the following update formula:

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)\lfloor x_i(t) - w_{ij}(t)\rfloor N(j,t) \qquad (14)$$

where w_{ij} is the *i*th component of the weight vector w_j, $\eta(t)$ is the learning rate and $N(j,t)$ is the neighborhood function (selection criteria);
5) repeat steps 2)-4) until no significant changes occur in the weights.

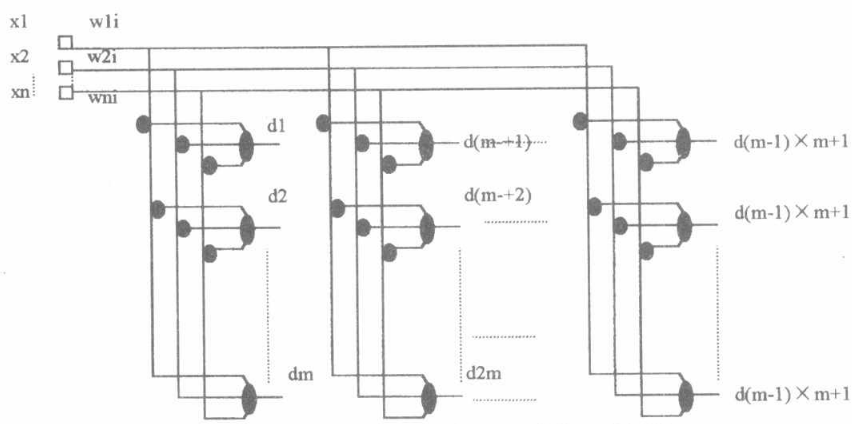


Fig.8. Network topology of the SOM.

VI. EXPERIMENTAL RESULTS

The fingerprint database used in the experiments was obtained from the U.S National Institute of Standards and Technology [6].
Five images were used for training. These are representing the basic five classes. To increase the database, different types of noise were added at different levels of signal-to-noise ratios. These types of noise are: Gaussian and salt & pepper noise [4]. Different levels of noise were added to the original fingerprint images to obtain signal-to-noise ratios that vary from 5 to 2. Forty different images were obtained by this procedure. The forty images were used in classification.
The results obtained show that the percentage of correct classification has been improved and reaches 97.5% compared to those obtained using the procedures described in [2]: 95% correct classification were obtained without the preprocessing procedure.

VII. CONCLUSION

Automatic fingerprints identification and classification systems are the most widely and accepted identification technique. Using an inverse filtering technique to restore the distorted areas in the fingerprint images combined with a self-organized feature map neural network, it has been able to obtain 97.5% correct classification. This results in a better recognition percentage compared to those obtained using the technique reported in [2] without a preprocessing procedure. The technique shows promise and the finding can be considered as a guide for further studies.

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