# FINGERPRINT RECOGNITION BASED ON SPECTRAL FEATURE EXTRACTION

*Nadder Hamdy[1], Magdy Saeb[2], Ramy Zewail[1], and Ahmed Seif[1]*
*Arab Academy for Science, Technology & Maritime Transport*
*School of Engineering,*
*1. Electronics Department 2. Computer Department*
*Alexandria, EGYPT*

***ABSTRACT***

With the advancements in computational techniques and computer technology, biometric authentication has a strong potential to be widely utilized in a variety of applications. Among various biometrics, fingerprint-based identification is the most mature and widely accepted technique.
In this work, we propose a fast procedure that exploits the spectral features of the fingerprint to obtain a compact descriptor representation that is both rotation and translation-invariant. Our experimental results show high matching accuracies that are equivalent or even better than those reported in the available literature.

***KEYWORDS:*** biometrics, fingerprint, recognition, Fourier transform, multi-resolution, descriptor.

## 1. INTRODUCTION

Traditional authentication approaches, such as passwords and ID cards, are becoming incapable to satisfy the high security requirements of some of today's applications. As an alternative, biometric information provides reliable identity-authentication capabilities. Physiological and behavioral characteristics that are used in biometrics, as shown in references [1], include the following facial features: eye features such as those associated with the retina and the iris, fingerprints, hand-geometry, voiceprints, gait, and gestures.

For a long time, fingerprints have been extensively used by forensic experts [2]. These are patterns of ridges and furrows on the surface of finger skin. The uniqueness of a fingerprint is determined by the overall pattern of ridges and furrows as well as local ridges anomalies that is known as the minutiae [3].

State-of-art fingerprint sensors are becoming smaller and cheaper. Sensors can now be incorporated into many applications such as mouse, and cellular phones. This constitutes a challenge to traditional fingerprint recognition approaches. Conventional recognition methods utilize minutiae, ridge endings and bifurcations, as the fingerprint features. The main steps for minutiae extraction are smoothing, local ridge orientation estimation, ridge extraction and minutiae detection. The matching process is done by comparing the minutiae list. A good quality fingerprint contains about 60 minutiae, but different fingerprints have different number of minutiae. Thus, the minutiae-based techniques have more consuming steps and rely heavily on the quality of the image. Moreover, the variable size of minutia-based representation makes it unsuitable for hardware oriented applications. Consequently, many algorithms have been developed to meet the requirements of modern applications [3]. Some of the promising techniques include applying the finite element technique to finger print identification as shown in [11].
To overcome some of the difficulties associated with traditional techniques, we have developed a robust procedure that captures relevant information by analyzing the fingerprint in the Fourier domain. This relevant information is stored in a vector form that is called the fingerprint descriptor. Section 2 discusses the spectral features of fingerprints. In section 3, we discuss the various building blocks of our approach. In section 4, we provide the results of our procedure when applied to a large fingerprint database [9]. A Summary and conclusion is shown in section 5.

## 2. SPECTRAL FEATUERS OF FINGERPRINTS

Analyzing the fingerprint texture in the Fourier domain was proposed by Coetzee and Botha in [4], and Willies and Myers in [5]. A fingerprint image consists mainly of valleys and ridges. The varying distances between the valleys and ridges gives rise to different frequency components. These different frequency components correspond to the minutiae and the structural distances and directions of the fingerprint, which differ from individual to another [6]. These properties suggest the possibility to extract meaningful information from the Fourier domain. Figure 1 shows two different fingerprint images and the corresponding Fourier spectrum.

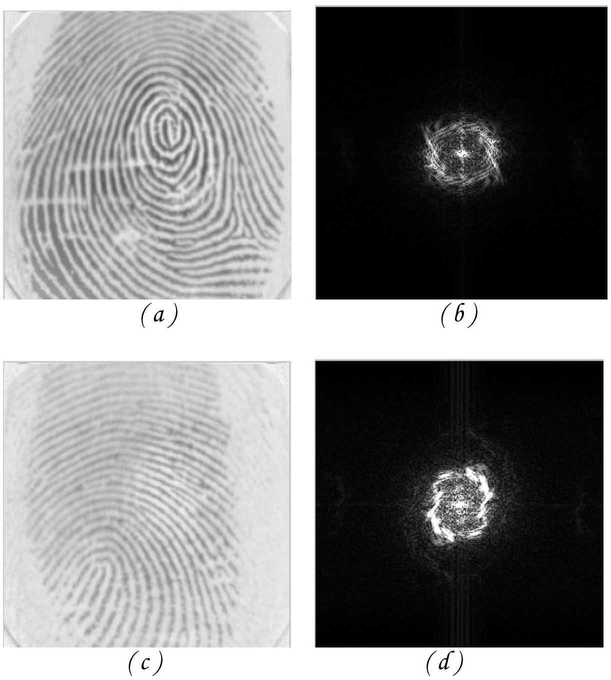


*Figure 1: Two different fingerprints (a) & (b) and their corresponding spectra (c) & (d)*

In the Fourier domain, the information within a fingerprint is contained within radial bands of frequencies whose angular extent follows from the predominant ridge orientation in the print [7]. Distinguishing characteristics of a fingerprint, such as ridge orientation and minutiae points, manifest themselves as small deviations from the dominant spatial frequency of the ridges [6]. This figure illustrates that the characteristic spatial frequency for each individual is located in the annular region, while low spatial frequency information at the center corresponds to background intensities.

Since each region in the fingerprint contributes to the whole Fourier domain, the magnitude spectrum is invariant to the translation of the finger. Consider an image b( x, y) which is a rotated and translated replica of a( x, y ). This relation is given by:

$$b(x,y) = a((\cos(\theta.y)) - \alpha, (-\sin(\theta.x) + \cos(\theta.y)) - \beta) \quad 2.1$$

where θ is the rotating angle, and (α, β) are the translation offsets. The Fourier Transforms; B (u, v) and A (u, v) of a(x, y) and b(x, y) respectively are related by:

$$B(u,v) = \exp(-j.\phi(u,v)).|A((u.\cos(\theta) + v.\sin(\theta) + v.\cos(\theta))| \quad 2.2$$

Where $\varphi_b$ (u, v) is the spectral phase of the image b(x, y). The Equation above shows that the magnitude spectrum, the absolute of B (u, v), is translation invariant. It is also clear from the equation that the rotation of the image a(x, y) rotates the spectral magnitudes by the same angle. This suggests that by using an appropriate feature extraction method, which seeks the information content in the spectrum, rotation- invariance can be achieved. The method will be discussed in section 3.5.

## 3. SPECTRAL FEATURES EXTRACTION

The main steps in our frequency-domain based identification algorithm are shown in block diagram in figure 2:

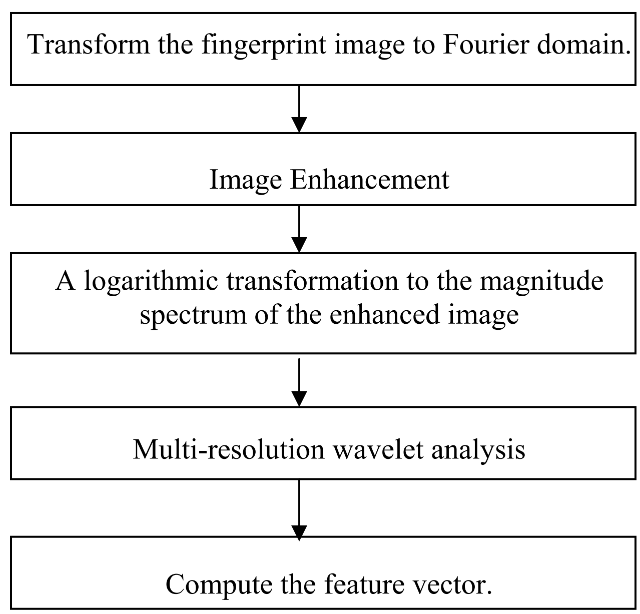


*Figure 2: Feature extraction block diagram*

### 3.1 Transformation to Fourier Domain

In this stage, the fingerprint image is transformed to frequency domain using the two-dimensional Fourier transform. The transform is given by:

$$F(k,l) = \frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} f(i,j).\exp(-j.2.\Pi.(\frac{k.i}{N}+\frac{i.j}{N})) \qquad 3.1$$

where f( i, j) is the image in the real space and the exponential term is the basis function corresponding to each point F( k, l) in the Fourier space. The spectrum is the magnitude of the complex function F (k,l). The spectrum is then shifted to have lower frequencies in the middle and higher frequencies towards the corner.

### 3.2 Image Enhancement

In order to facilitate the feature extraction stage, enhancement has to be done to eliminate noise and background patterns. Enhancement is completed using spectral analysis techniques. The fingerprint features are characterized by certain frequency components of clouds in the spectrum. Applying a suitable mask to the spectrum would enhance certain frequencies and remove others [8].

We have applied a high-pass filter to remove the low frequency components that correspond to the background intensity and are irrelevant to the identification process. The high-pass filter is defined as a small transfer function values located around the origin or the low frequency side. The large values are located outside this area. The filtering process in the frequency domain is performed using the following two steps: transform image to Fourier domain, and then multiply image spectrum by the high-pass Butterworth filter mask. The process of filtering in the frequency domain is shown in Figure 3.

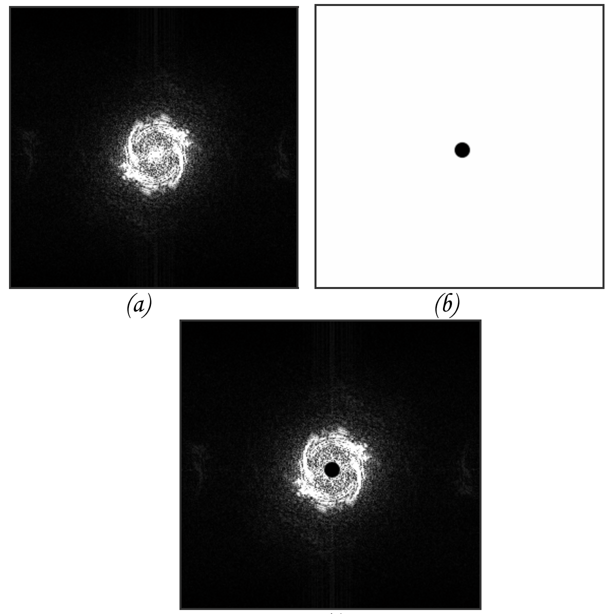


*Figure 3: How Images are filtered in the frequency domain (a) Original image spectrum, (b) High-pass Butterworth filter mask, (c) High-pass filtered Spectrum*

Figure 4 illustrates the effect of high pass filtering on the image in the spatial domain.

*Figure 4: A high pass filter applied to fingerprint image*

### 3.3 Logarithmic Transformation

A logarithmic transformation is then applied, that is the magnitude spectrum of the enhanced image, is mapped to a log scale. This takes the form:

$$F_{\log}(u,v) = 20.\log(|F(u,v)|) \qquad 3.2$$

Where | F (u , v) | is the magnitude spectrum of the fingerprint. This is done to compress the dynamic range of the spectrum and prevent high intensity values to dominate.

### 3.4 Multi-resolution wavelet analysis

Multi-resolution analysis transforms an original signal into a hierarchical representation at different scales. The wavelet transform fulfills this property by decomposing the original signal into its approximations and details, and iterates the decomposition process on these approximation signals. Given any function that lies in the set of finite energy functions, it can be represented as:

$$f(x,y) = \sum_{(i,j)} a_{M,i,j}\phi_{M,i,j} + \sum_{m=1}^{M}\sum_{(i,j)}\sum_{k=1}^{3} d^{k}_{m,i,j}\psi^{k}_{m,i,j} \tag{3.3}$$

where $a_{M,i,j}$ and $d_{m,i,j}$ are the approximation and wavelet detail coefficients respectively. $\Phi$ and $\psi$ are the scaling and wavelet basis respectively. M represents the highest decomposition level of the wavelet transform. The first term in the equation above is the approximation of the signal at level M while the second represents all of the wavelet detail coefficients from level 1 to M.

In this stage, multi-resolution wavelet decomposition is applied; the approximation at the highest level is used in the feature extraction stage. The performance of different wavelet families has been investigated. The three wavelet filters used in the experiments are Haar; Daubchies-4 and Coiflet-3.Each type of wavelets has its own significance and drawbacks.
The Haar wavelet is the oldest and simplest wavelet. Some of the advantages of Haar are that it is orthogonal and has a very short support length. Therefore, it is the only wavelet that allows perfect localization in the transform. However, the magnitude response of the Haar filters does not eliminate mid-band and high frequencies but only attenuates it. On the other hand, Daubechies wavelet has a longer compact support. Consequently, its low and high pass filters resemble ideal filters more than those of the Haar transform. Accordingly, it is a better frequency extractor. On the other side, Daubechies wavelet is not symmetric. The projection of the signal on this biased function leads to "information shift". This shift is adverse in locality analysis. Coiflet wavelet is nearer to symmetry. Hence, it will not weight the signal to any direction, that is no signal bias, and no shift will occur [10]. A more detailed discussion, for how different wavelet families affect the system performance, is presented in section 4.

### 3.5 Generation of the Feature vector or descriptor

Features are extracted from the image approximation at the highest resolution level. Consequently, we obtain a map of the deviations of the spectrum frequencies from the dominant spatial frequency. This map is then converted to a one dimension vector, sorted and the highest coefficients are selected. A feature vector of length 500 is obtained for every fingerprint image.

## 4. EXPERIMENTAL RESULTS

Our experiments were done on a database containing 300 images (size = 300 x 300) from 100 different fingers, 3 impressions from each finger. The images were captured with a low cost optical sensor. More information about the database can be found in [9].
The following procedures were carried to evaluate the system performance. Each fingerprint in the database is matched with all other images using the Euclidean distance. The distributions of the Genuine and Imposter matching were then estimated as shown in figure 5.

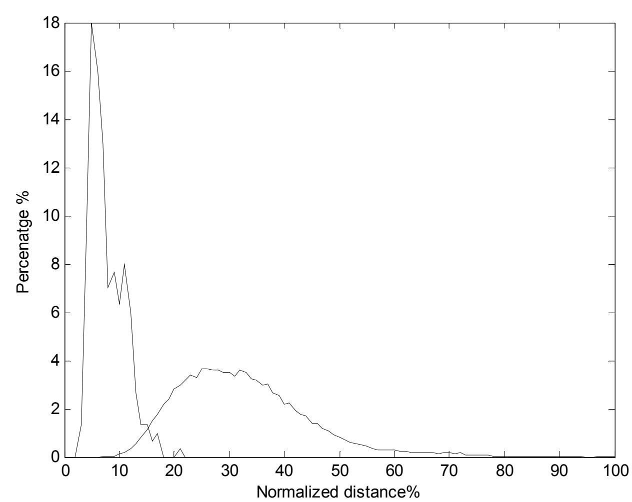


*Figure 5: Gunine and Imposter Distribution*

For a given distance threshold, the genuine accept rate and false accept rate were calculated. The overall system performance was evaluated using the Receiver Operating Characteristic (ROC) curve, that is a plot of

Genuine Acceptance Rate(GAR) against False Acceptance Rate (FAR) for all possible distance thresholds. Figure 6 demonstrates that the adopted method has achieved high GAR at low FAR.

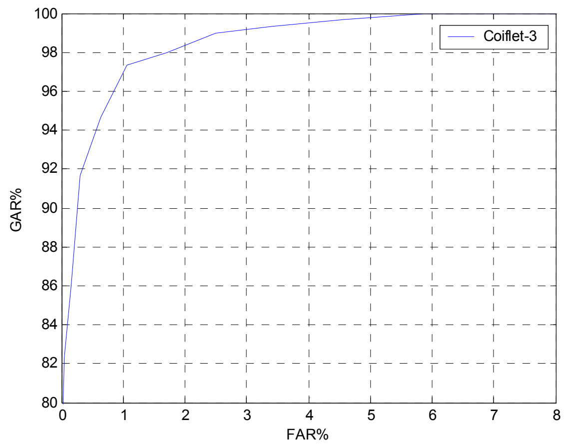


*Figure 6: ROC curve (FAR against GAR)*

As mentioned in section 3.4, different wavelet families have been tested for the multi-resolution analysis stage. The three wavelet families used in our experiments are: Haar, Daubechies-4, and Coiflet-3. Experimental results showed that there was a variation in the overall system performance when a specific family was employed. Figure 7 shows the system performance using the different families.

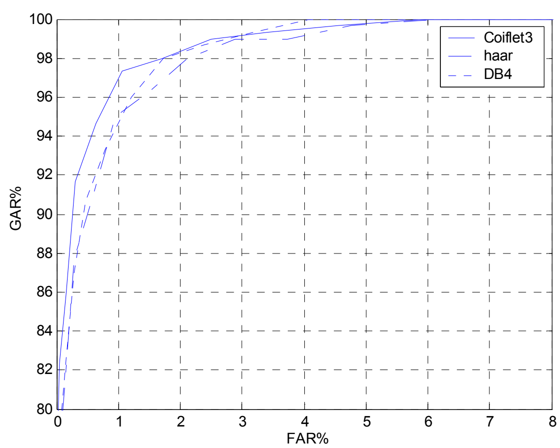


*Figure 7: Overall system performance using different wavelet families.*

The ROC curves show that our system performance depends, to some extend, on the wavelet family used in the multi-resolution analysis stage. Coiflet-3 filters seem to be a good choice when the system requires low FAR less than 2 %. On the other side, Db-4 filters seem to be a better choice when system performance requirements are less demanding on FAR, greater than 2.8 %.

## 4. Conclusions and Future Work

In this paper we have developed a modified technique for automatic fingerprint identification. The technique is based on spectral feature extraction of the fingerprint. The method achieved a compact representation that is both rotation and translation-invariant. Moreover, the fixed length feature vector and the relatively simple computations encountered in the feature extraction and matching phases give rise to the suitability of the proposed procedure for hardware implementation.

Currently, we are working on:

i- A robust representation to deal with poor quality fingerprint images.

ii- Utilizing the multi-resolution wavelet analysis stage to achieve a "coarse to fine" multi-resolution matching strategy.

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