

# ALGORITHMS FOR BINARIZING, ALIGNING AND RECOGNITION OF FINGERPRINTS

A. Pillai, S. Mil'shtein and M. Baier

*Advanced Electronic Technology Center, ECE Dept., University of Massachusetts, 1 University Ave, Lowell, MA U.S.A.*

**Keywords:** Fingerprints recognition, Binarizing, Alignment, Fourier transform.

**Abstract:** Minutiae based algorithms are widely used today for fingerprint authentication. In this study, we report the use of the Fast Fourier Transform (FFT) as a base principle for our recognition method, and have also developed image normalization methods. We also developed a novel method to align fingerprints to a common reference orientation based on the Fourier Mellin Transform. Two methods for image recognition are described. The first method uses image subtraction techniques in conjunction with a thresholding scheme. The second method, which is currently in development, utilizes multiple neural networks running in parallel. This technique is expected to be able to run image comparisons on large databases in real-time through the use of modern parallel processing technology. In this study we analyzed 720 fingerprints generated by wet-ink, flat digital scanners, and by a novel touch less fingerprinting scanner. For the image subtraction method comparing high quality fingerprints (prints taken in touch less way), the rate of success is 97%. For poorer quality prints, (those taken with wet-ink) the rate of success dropped to 93%. Recognition statistics are not currently available for the neural network based image recognition method as it is currently in development.

## 1 INTRODUCTION

Fingerprints offer a unique method for personal identification. Fingerprints afford an infallible means of personal identification, because the ridge arrangement on every finger of every human being is unique and does not alter with growth or age. Fingerprint authentication is the most preferred method because of their distinctiveness and persistence over time as specified by Maltoni (2003). The individuality of fingerprints has been discussed in detail by Pankati (2001). It has served almost all the governments worldwide over many years to provide accurate identification of criminals. No two fingerprints have been found to be the same in the billions of comparisons that have been done to date unless they belong to the same person. It outperforms DNA and other human identification systems to identify more number of criminals.

The minutiae algorithm is widely used for fingerprint authentication. Minutiae points are local ridge characteristics that appear as either a ridge ending or a ridge bifurcation. A complete fingerprint consists of about 100 minutiae points in average. The measured fingerprint-area consists in average of

about 30-60 minutiae points depending on the finger and on the sensor area. These minutiae points are represented by a cloud of dots in a coordinate system. They are stored together with the angle of the tangent of a local minutiae point in a fingerprint-code or directly in a reference template. A template can consist of more than one fingerprint-code to expand the amount of information and to expand the enrolled fingerprint area. In general this leads to a higher template quality and therefore to a higher similarity value of the template and the sample. To overcome the drawbacks of minutiae, hybrid methods have been proposed in Jain (2001).

There are many challenges that need to be overcome when developing an algorithm which is to be used for reliable recognition of fingerprints recorded by different technologies. This is because different fingerprint capture techniques create different representations of a given finger. These challenges include different format size of images, non-linear distortions of fingerprint ridges, differences in orientation, and variation of gray scale values.

In the current study, we use the Fast Fourier Transform (FFT) as a base principle for our novel

recognition method. We have also developed a new binarization method that is used to eliminate variations in gray scale levels of each image, leaving the resulting images looking like a traditional ink rolled fingerprint. In this study we analyze 720 fingerprints generated by wet-ink, flat digital scanners, taken from FVC 2004 and by the novel contactless fingerprinting scanner described in Palma (2006) and Mil'shtein (2008). In section 2, we describe the binarization steps, section 3 contains description about the fingerprint alignment process and section 4 contains information about the recognition procedure.

## 2 BINARIZATION PROCEDURE

Most fingerprint recognition algorithms currently being used, including the widely used minutiae algorithm, rely on the specificity of ridge endings and ridge bifurcations. Because of this, it is necessary to clearly define the fingerprint ridges and valleys using only two distinct values, this process is called binarization, and is one of the most important steps that precede the recognition stage. Regardless of the quality of any image recognition algorithm, a poorly binarized image can compromise its recognition statistics.

A good binarization algorithm would give an image which would have very clear and uniform black ridges on a white background even if the image is overexposed to a certain degree. In the current study the following binarization techniques are used:

- 1) Region-Based thresholding
- 2) Filter-Based mentioned in Meenen (2005)

The first step is to divide the image into an  $N$  by  $N$  grid of smaller blocks. Then the ridges like regions within these smaller blocks are determined. This is done by taking the gradients in the  $X$  and  $Y$  direction and then finding the co-variance data for the image gradients. Once this step is completed, the orientation of ridges is computed. Estimation of ridge frequencies in these blocks follows. For this, first the mean orientation within the block is obtained. Then the image block is rotated so that the ridges are vertical. The rotated image is then cropped so that it does not contain any invalid regions. A projection of the grey values, down the ridges, is obtained by summing down the columns. Peaks in projected grey values are found by performing grayscale dilation and then finding where the dilation equals the original values. The

spatial frequency of the ridges is determined by dividing the distance between the 1st and last peaks by the number of peaks. If no peaks are detected, or the wavelength is outside the allowed bounds, the frequency image is set to 0. The ridges are then enhanced with the help of a median filter. The image obtained after this process is thresholded to obtain the binary fingerprint. The threshold for binarization depends on the resolution for the image.

We found that this technique works best with the images that are obtained from the contactless fingerprinting system described in Mil'shtein (2008). This binarization technique is largely invariant to inconsistencies in brightness levels throughout the image, and results in a binary image that has consistent information throughout. It should be mentioned at this point that the downside of this process is that a relatively large number of calculations are needed, which adds to the time needed for the overall recognition algorithm to complete. In section 6 we give recommendations on image registration procedures, but for now it is recommend that all images that are to be stored in a database be stored (at minimum) in their binary forms to reduce computations when comparing fingerprint images.

## 3 FINGERPRINT ALIGNMENT

Fingerprint alignment is an important stage that precedes fingerprint recognition. It is important because no matter which algorithm is being used for recognition, one must be sure that the regions being compared are the same. Fingerprint alignment using eight special types of ridges extracted from thinned fingerprint image is reported in Hu (2008). Other alignment techniques based on phase correlation of minutiae points as described in Chen (2007), using line segments as pivots based on minutiae as mentioned in Carvalho (2004) and using similarity histogram detailed by Zhang (2003), have also been reported. But their inherent dependence on minutiae necessitates a need for a new novel alignment technique not based on minutiae. In this study, an alignment technique based on the Fourier Mellin Transform will be described.

The Fourier-Mellin transform is a useful mathematical tool in image processing because its resulting spectrum is invariant in rotation, translation and scale. The Fourier Transform itself (FT) is translation invariant. By converting the resulting FT to log-polar coordinates, we can convert the scale and rotation differences to vertical and horizontal

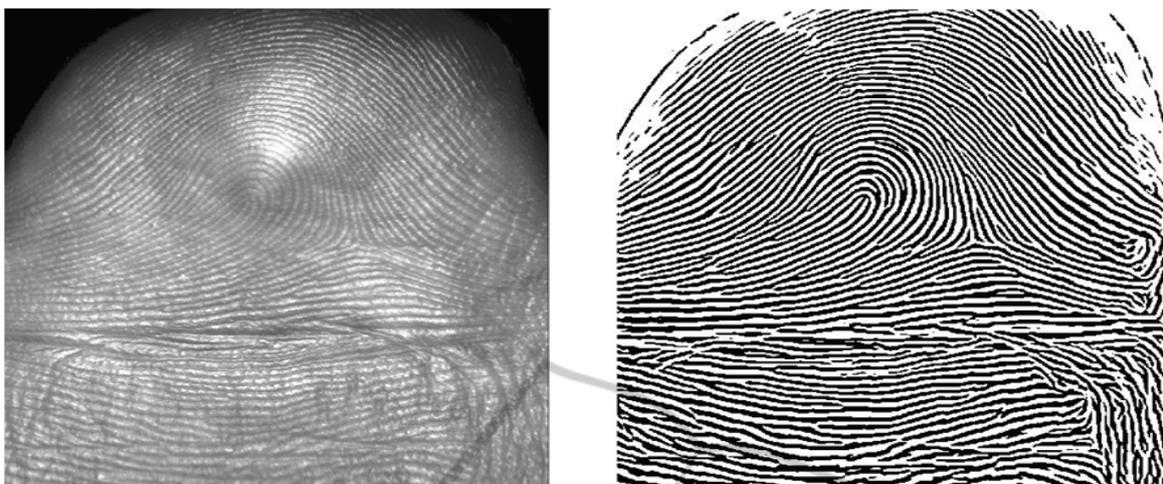


Figure 1: Grayscale image of a selected fingerprint (Left) and the corresponding binarized image (Right).

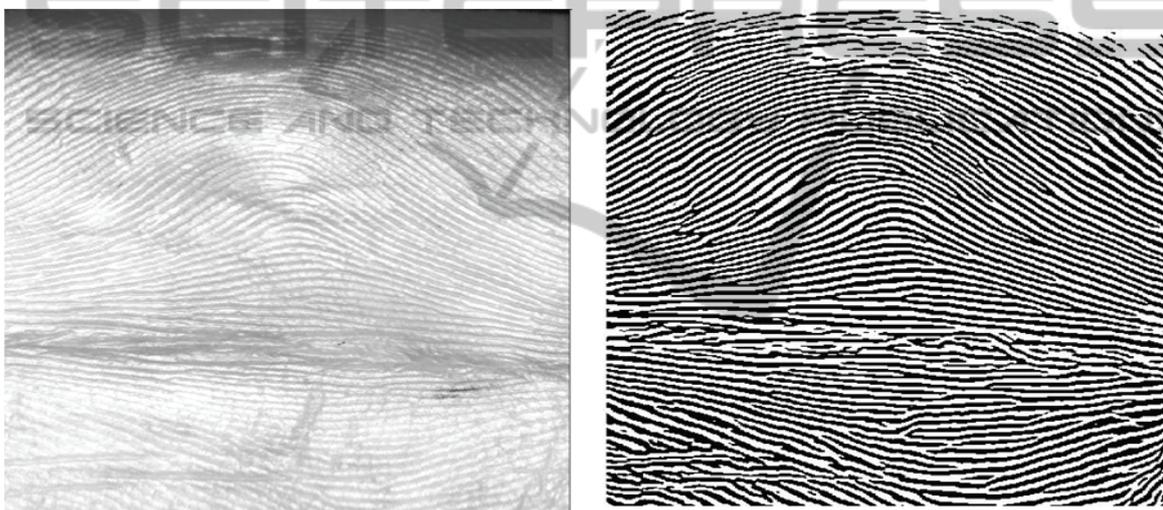


Figure 2: Strength of binarization even if the image is seemingly overexposed.

offsets that can be quantified. A second transform, called the Mellin transform (MT), gives a transform-space image that is invariant to translation, rotation and scale. An application of the Fourier-Mellin Transform for image registration can be found in Guo (2005).

The Mellin transform can be expressed as:

$$M(u, v) = \int_0^\infty \int_0^\infty f(x, y) x^{-ju-1} y^{-jv-1} dx dy ; \forall x, y > 0 \tag{1}$$

Convert to polar coordinates using:

$$r = \sqrt{x^2 + y^2} \tag{2}$$

We now have:

$$M\{f(r)\} = \int_0^\infty f(r) r^{-ju-1} dr \tag{3}$$

Making  $r = e^\gamma$  and  $dr = e^\gamma d\gamma$  we have :

$$M\{f(e^\gamma)\} = \int_{-\infty}^\infty f(e^\gamma) e^{-ju\gamma} d\gamma \tag{4}$$

By changing coordinate systems from Cartesian to a Log-Polar system, we can directly perform a DFT over the image to obtain the scale and rotation invariant representation. The figures below show some of the results of the alignment using the Fourier-Mellin transform on images taken from Palma (2006).

The inverse Fourier transform of the Mellin Transformed images helps to see how well the image is aligned with respect to the base image. While this step is necessary to see the alignment results, the Fourier transforms are stored in a separate database as from here they are now the

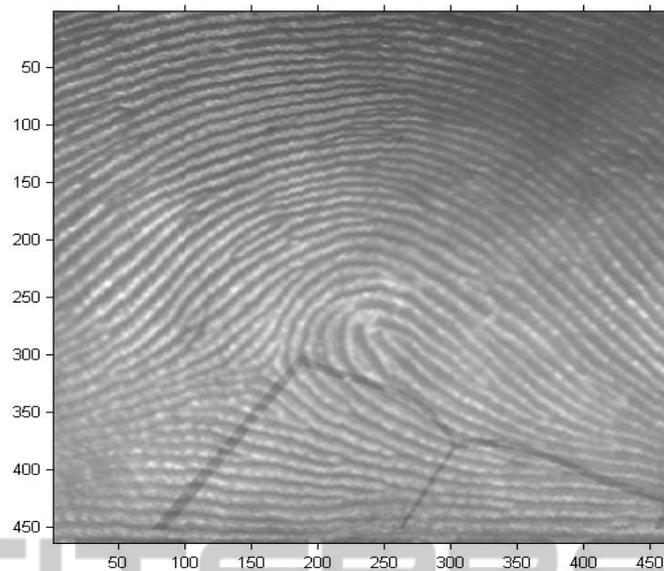


Figure 3: Image of the 1<sup>st</sup> fingerprint.

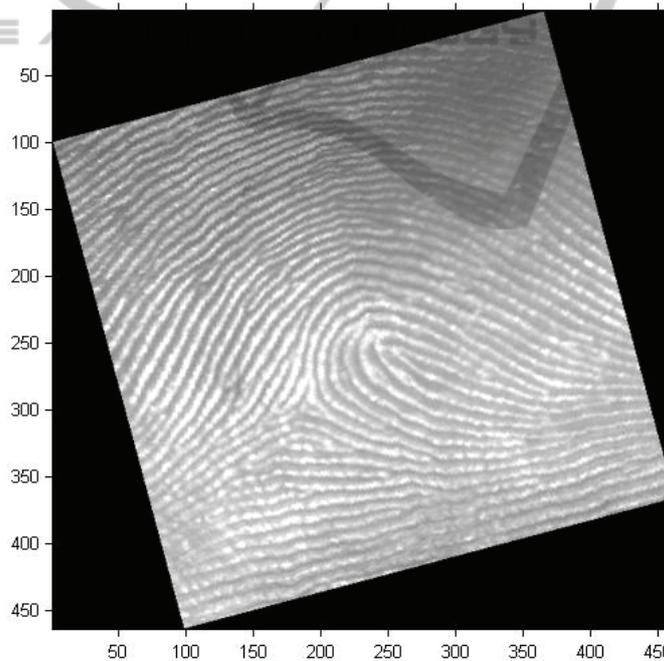


Figure 4: Image of 2<sup>nd</sup> fingerprint (In need of alignment).

templates that will be used for comparison. This will eliminate the need to take again the FFT of the aligned image and the base image when it comes to comparing the fingerprints.

#### 4 REGISTRATION PROCEDURES

To run a fingerprint recognition system in its most efficient state, steps should be taken within image registration procedures to ensure that all possible normalization of images and image transforms are

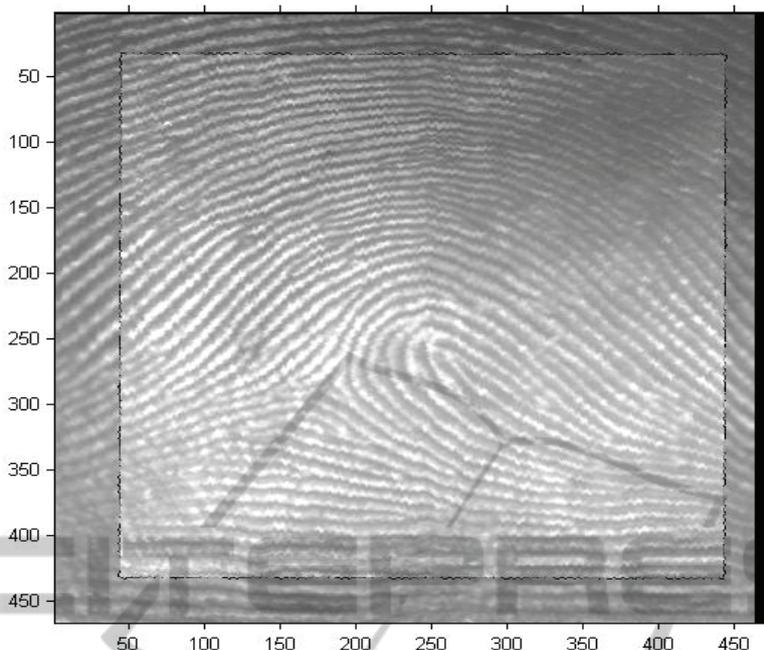


Figure 5: Aligned 1<sup>st</sup> and 2<sup>nd</sup> images (Image 2 superimposed upon image 1).

done upon image registration and not at the time of image recognition. This way when it is time for actual image comparison, fewer calculations will need to be performed, greatly increasing the throughput of the algorithm. For this reason, we recommend the following image registration procedures.

It should be the normalized frequency domain image that should be stored in the database rather than the original or binarized image. This allows the pattern recognition engine to directly take the image data for use in comparison without the need for any preprocessing steps. We recommend that as a new image is acquired, it is processed and stored as shown in figure 6.

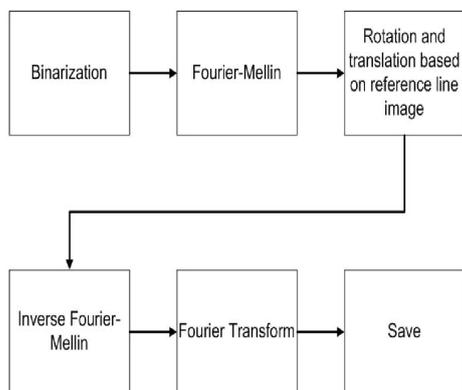


Figure 6: Image registration procedure.

## 5 RECOGNITION ALGORITHM

There are three types of algorithms used for fingerprint matching briefly described by Prabhakar of MSU:-

### a) Correlation based Algorithm:-

Here two fingerprints are superimposed on each other and the correlation at intensity level between corresponding pixels is computed.

### b) Minutiae based Algorithm:-

Minutiae points are first determined on a fingerprint. In order to make a comparison, 21 points are needed. Minutiae points are nothing but points where there is a ridge ending or a ridge bifurcation. In this process, the minutiae points are stored as sets of points in a two dimensional template. Then the algorithm finds the alignment between the template and the input set of minutiae sets that result in maximum number of pairings. This stage requires the operator intervention.

### c) Ridge Feature based Matching:-

Here fingerprints are compared based on the features extracted from the fingerprints.

In this study we report on the development of an algorithm based on taking the Fast Fourier Transform (FFT) of images and using a thresholding scheme for comparison. It should be mentioned here

that there are drawbacks to using a thresholding scheme, and we are currently developing a neural network based pattern recognition engine which can take advantage of modern day parallel processing. We expect to largely decrease the time necessary to compare multiple images within a database, hopefully opening up a door for large database, real-time fingerprint recognition applications.

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the *Fourier* or frequency domain. The DFT is the sampled Fourier Transform and therefore does not contain all frequencies forming an image, but only a set of samples which is large enough to fully describe the spatial domain image. The number of frequencies corresponds to the number of pixels in the spatial domain image, i.e. the image in the spatial and Fourier domain is of the same size.

For a square image of size  $N \times N$ , the two-dimensional DFT is given by:

$$F(k, l) = \frac{1}{N^2} \sum_{a=0}^{N-1} \sum_{b=0}^{N-1} f(a, b) e^{-i2\pi(\frac{ka}{N} + \frac{lb}{N})} \quad (5)$$

Where  $f(a, b)$  is the image in the spatial domain and the exponential term is the basis function corresponding to each point  $F(k, l)$  in the Fourier space. The equation can be interpreted as: the value of each point  $F(k, l)$  is obtained by multiplying the spatial image with the corresponding base function and summing the result.

It is this frequency domain image that should be saved as the reference information for registration of a new fingerprint to a database. By saving this image rather than the raw, oriented, or binarized images which resulted from the previous steps one can minimize the number of calculations necessary when the time comes for actual fingerprint comparison.

Image comparison is currently done by comparing the frequency domain images element by element to see which have a similar value. Based on the similarity of these values, a counter is incremented and once this value crosses a statistically determine threshold, a match is declared. We are working on increasing the database so that we can provide ROC and CMC datasets and curves and test the performance on a wider database. For high quality fingerprints (prints taken touch less way), the rate of success is 97%. For poorer quality prints, (those taken with wet-ink) the rate of success of our algorithm is 93%. The advantage of this method of comparison is that it is independent of minutiae

points and more reliant on the ridge patterns. If the fingerprint is distorted with pressure induced distortion then this algorithm can be used to determine a match. We continue to increase the database for analysis by our recognition algorithms. A pattern recognition engine should be present in the recognition stage to successfully compare an image with a large database. The drawbacks of this algorithm would be the time taken to come to a decision and the requirement that the images compared be of the same size.

We are currently developing a neural network based approach for pattern recognition within fingerprint images. Neural networks consist of highly interconnected processing elements called neurons which are all interconnected acting in parallel to solve a common goal. This methodology lends itself to parallel processing, and can take advantage of modern day parallel processing hardware, creating the opportunity for image comparison in real-time even when comparing large databases. The system in development currently divides the images in a database into sets of approximately 200 images, and trains one neural network per image set utilizing an automated training process described in Masters (1993). The utilization of neural networks allows the system to be optimized to run on high throughput graphics processing units (GPU's). By selecting the number of neurons in the network to be equal to the number of pixels in the frequency domain images being compared, a direct image-to-image comparison can be done in one GPU clock cycle. Each network is capable of comparing approximately 200 images accurately, and the number of networks in parallel is limited by the number of GPU's in the system. By creating many neural networks, all autonomously trained, we expect to be able to create a real-time fingerprint recognition system for large-scale databases.

In Gour (2010), the fingerprints are recognized by using Monolithic and Modular Neural Network. A monolithic neural network is one that takes an input vector  $X$  and produces an output vector  $Y$ . The relationship between  $X$  and  $Y$  is determined by the network architecture. It generally consists of three layers: one input layer, one output layer and more than one hidden layer. The Backpropagation neural network is an example of the monolithic network. The training of a backpropagation network involves three stages: the feedforward of the input training patterns, the calculation and backpropagation of the associated error and the weight adjustments. Backpropagation network is trained for query

fingerprint to match it among a large number of stored fingerprints as is evident in Jin (2002). The average training time is 44.7 secs and the accuracy is 98%.

In the modular approach, one task is decomposed into subtasks, and the complete solution requires the contribution of all modules. To train a modular neural network, which is having N number of modules (feature points) in a particular fingerprint requires two steps: Training of small modules and training of intermediary modules. All the modules are trained by using the backpropagation neural network algorithm specified by Gour (2005). The average time taken is 1.84 secs and the accuracy is 100%. Due to modularity, the modular neural network gives better performance as compared to monolithic networks.

## 6 CONCLUSIONS

We reported the development of a novel fingerprint normalization and authentication algorithm which has binarization, alignment, and recognition stages. It is important to note that our method of fingerprint image processing requires organization of database. Structuring of database is orientation of all fingers with regards to the position of the reference delta. Although, we are suggesting a quality control in our flow of processing to be done by Inverse Mellin Transform, this step is more precautionary method. Unlike, widely distributed minutiae based fingerprint processing; our method does not require interference of operator or final analysis by an operator. We also continue to increase the database so that we can provide ROC and CMC datasets and curves and test the performance on a wider database. Well known development of neural networks for processing of massive image files can be easily used in our method. The neural network is expected to shorten the processing time significantly. We also report the beginnings of a neural network based recognition engine running on parallel GPU's, which is expected to enable real-time image recognition on large databases. Finally, the recommended image registration procedures are outlined which are designed to optimize performance of the image recognition algorithm by decreasing the number of calculations necessary for image comparison.

## REFERENCES

Maltoni, D., Maio D., Jain A. K., Prabhakar S., 2003,

- Handbook of Fingerprint Recognition* Springer-Verlag, New York,
- S. Pankanti, S. Prabhakar, A. K. Jain, CVPR 2001 Volume 1, 2001 pp 1-805-1-812 vol.1. "On the individuality of fingerprints" Proc of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition.
- Anil Jain, Arun Ross, Salil Prabhakar, 2001, pp. 282-285, "Fingerprint Matching using Minutiae and Texture Features" Proc. of international conference on Image Processing.
- Palma J, Liessner C, Mil'shtein S, 2006, "Contactless Optical Scanning of Fingerprints with 180° View" Scanning, 28, 6, pp 301-304
- S. Mil'shtein, J. Palma, C. Liessner, M. Baier, A. Pillai, and A. Shendye, 2008, "Line Scanner for Biometric Applications" IEEE Intern. Conf. on Technologies for Homeland Security, ISBN 978-1-4244-1978-4 P 205-208.
- P. Meenen, R. Adhami, 2005, "Approaches to image binarization in current automated fingerprint identification systems", Proceedings of the Thirty-Seventh Southeastern Symposium on System Theory, ISBN: 0-7803-8808-9
- C. Hu, J. Yin, E. Zhu, H. Chen, Y. Li, 2008, "Fingerprint Alignment using Special Ridges" ISBN 978-1-4244-2175-6
- W. Chen, Y. Gao, 2007, "Minutiae-based Fingerprint Alignment Using Phase Correlation", Mechatronics and Machine Vision in Practice, Springer Link, pp 193-198,
- C. Carvalho, H. Yehia, 2004, "Fingerprint Alignment using Line Segments", Biometric Authentication, Springer, pp 1-10
- T. Zhang, J. Tian, Y. He, J. Cheng, X. Yang, 2003, "Fingerprint alignment using similarity histogram", International conference on audio and video-based biometric person authentication, pp 854-861
- Xiaoxin Guo Zhiwen Xu Yanan Lu Yunjie Pang, Sep 2005, "An Application of Fourier-Mellin Transform in Image Registration", The Fifth International Conference on Computer and Information Technology, pp 619-623.
- S. Prabhakar, A. Jain, "Fingerprint Identification", <<http://www.cse.msu.edu/biometrics/fingerprint.html>>
- Masters, Timothy, 1993, "Practical Neural Network Recipes in C++" ISBN: 0-12-479040-2
- B. Gour, T.K. Bandopadhyaya, R. Patel, 2010, "ART and Modular Neural Network Architecture for multilevel Categorization and Recognition of Fingerprints", 2010 Third International Conference on Knowledge Discovery and Data Mining, pp 536-539
- A. L. H. Jin, A. Chekima, J. A. Dargham, L. C. Fan, 2002, "Fingerprint Identification and Recognition using Backpropagation Neural Network", Proceeding of Student Conference on Research and Development, pp 98-101
- B. Gour, et. Al, 2005, "Fast Fingerprint Identification System using Backpropagation Neural Network and Self Organizing Map", Proc. Of Glow Gift., International Level Seminar.