

Adaptive Fingerprint Pore Model for Fingerprint Pore Extraction

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Abstract —

A reliable Adaptive anisotropic pore model for extracting pores from fingerprint image is presented in the paper. The pore model utilizes the ridge orientation for pore extraction. The fingerprint image is divided into blocks and average squared gradient method is used to compute ridge orientation. Ridge frequency used for image filtering is obtained by counting the number of pixels between two consecutive peaks within each block of fingerprint image. According to the ridge orientation and frequency, Gabor filter is obtained for each well defined block. The ridge map resulting from Gabor filters is used to remove the spurious pores at the post processing stage. Experiments were conducted on a high resolution partial fingerprint database.

Keywords—Ridge Orientation, ridge frequency, Gabor filter, Pore extraction.

I. Introduction

Fingerprints have been accepted worldwide as a reliable biometric characteristic and used for person identification. One of the important features that separate fingerprint from others is its uniqueness and stability [1]. This has led to the adoption of fingerprint recognition in the field of forensic, law enforcement and many other applications. The Law enforcement agencies and forensic departments routinely use fingerprint for the identification of criminals and victim. But they mostly rely on the minutia features present on fingerprint for recognition. However with the advancement in the quality of images it has become possible to reliably extract the pores for matching along with the minutia. Pore matching along with the minutia has significantly improved the efficiency of fingerprint matching.

Fingerprint image is composed of black and white line structure often called as ridges and valleys, out of which ridges are of key interest. Based on this ridges pattern and their appearance fingerprint features are generally classified into three levels [2]. Level 1 feature is characterized by ridge flow pattern such as orientation field and singular points. The ridge pattern includes whorl, left loop, loop, arch, tented arch and the singular points includes core and delta points. Level 2 features also called as minutiae refers to ridge endings and bifurcations. Level 3 features include pores, dots, ridge contour and incipient ridge which are the fine details on fingerprint ridge requires a high resolution images for their modeling.

Pores are the circular dots that resides on the fingerprint ridge and often called as sweat pores. If a pore is exuding perspiration then it is a opened pore and is connected to one or two neighboring valleys. On the other hand a closed pore appears as an isolated dot on the ridge [11]. Along the ridge tangential direction, the intensity profile across the pore has a Gaussian shape. Fig 1. shows the spatial appearance of pore, Dots and incipient ridges on the fingerprint ridge.

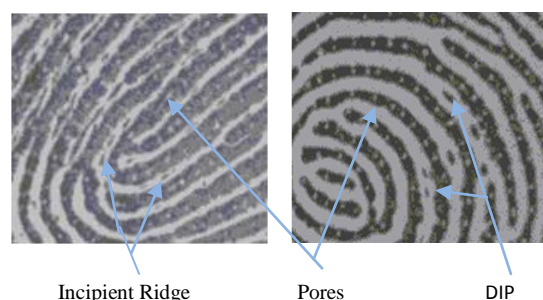


Fig 1. Level 3 Features [6]

The main subject of the proposed pore model is to model the spatial appearance of pore in a fingerprint image and detect them with filters. The filtering based approaches are more efficient and more robust. An important step in the pore based fingerprint recognition system is the efficient extraction of pores. Pore position on the fingerprint ridge plays an important role during pore extraction because the shape and size of pore can vary from one fingerprint to other. The proposed pore model irrespective of pores shape and size reliably and efficiently detects them.

The rest of the paper is organized as follows. In section 2 fingerprint orientation field estimation using gradient method is presented. Section 3 introduces the ridge frequency estimation using ridge count method. In section 4 coherence of fingerprint image is obtained. Section 5 describes the

filtering of image using Gabor filter. Section 6 presents the pore extraction algorithm using anisotropic pore model. Section 7 describes the pore extraction process. Section 8 performs experiments on the high resolution partial. Section 9 concludes the paper.



Fig 2. Estimation of Orientation Field; (a) Input fingerprint image; (b) Orientation field for 17×17 block; (c) coherence for 5×5 block [8]

II. Estimation of Orientation Field

Orientation field describes the ridge flow pattern in the fingerprint image. Since the ridges are of key interest in fingerprint image, ridge orientation field estimation has been incorporated in most of the fingerprint recognition algorithm as an initial and important stage. The approach used here for extracting the ridge orientation field is based on the average squared gradient method.

As per [3], orientation field is aligned at an angle of 90 degree to the gradients. Hence the orientation field is estimated using gradients, which is based on the Principal Component Analysis (PCA). A 2-dimensional Gaussian joint probability density function is computed from the gradients when PCA is applied to the covariance matrix of these vectors. The average ridge orientation is given by the axis of the probability density function. Estimation of orientation field involves dividing the fingerprint image into non overlapping block of size $w \times w$. Zhao et al. Zhao et al. [5] initially estimated the ridge orientation pixelwise instead of blockwise, which is very time consuming when dealing with high resolution images of 1000ppi or more. Ridges run nearly parallel with each other in a local region of fingerprint and thus blockwise approach does not affect the result, rather reduces the computational time.

Ratha et al.[4] efficiently obtained the dominant ridge orientation in a 16×16 block. For the estimation of orientation field following steps were employed. Fingerprint image is divided into $w \times w$ non-overlapping blocks. Gradient magnitude in x and y

direction are estimated within each block using 3×3 sobel mask.

Let ∂_x and ∂_y be the gradients within a block centered at pixel (i, j) . The ridge orientation of the image is estimated using the following expression:

$$\theta(i, j) = \frac{\pi}{2} + \frac{1}{2} \tan^{-1}(2G_{xy}, G_{xx} - G_{yy}) \quad (1)$$

$$G_{xx}(i, j) = \sum_{h=-w/2}^{w/2} \sum_{k=-w/2}^{w/2} \partial_x(i+h, j+k)^2 \quad (2)$$

$$G_{yy}(i, j) = \sum_{h=-w/2}^{w/2} \sum_{k=-w/2}^{w/2} \partial_y(i+h, j+k)^2 \quad (3)$$

$$G_{xy}(i, j) = \sum_{h=-w/2}^{w/2} \sum_{k=-w/2}^{w/2} \partial_x(i+h, j+k) \cdot \partial_y(i+h, j+k) \quad (4)$$

The orientation field obtained using the above equation is shown in the Fig.2 (b). The Block size could be of 16×16 or 32×32 . Here we have used the block size of 41×41 so as to get the center pixel of block because the even valued blocks does not have an exact center.

III. Reliability

The Reliability is used to get the certainty of the ridges in the fingerprint image. In other word it is used to indicate whether the gradients are aligned in the same direction or not. The reliability is 1 where

gradients are parallel to each other and 0 where they are not parallel to each other or distributed over all structure tensor. A structure tensor matrix of 2×2 is computed for each block and the two Eigen values resulting from the matrix is used to estimate the reliability. Bazen et al. [3] computed the reliability based on the gradient parameters which were calculated in the orientation field estimation. The expression for reliability is given below.

$$R_{i,j} = \frac{\sqrt{(G_{xx} - G_{yy})^2 + 4G_{xy}^2}}{G_{xx} + G_{yy}} \quad (5)$$

For a large size of block the reliability is not accurate, thus a small size of block is preferred. Pixel-wise computation of reliability gives better results with increase in the cost of the computation time for a high resolution image. Fig 2(c) shows the coherence computed over block of 5×5 .

IV. Estimation of Ridge Frequency

The Fingerprint ridge frequency along with the ridge orientation serves as parameters for image filtering in the filtering section. Ridge frequency is the measure of number of pixels located between the two consecutive peaks, computed over a rotated block which is of larger dimension than the block of image. The block rotation is specified by the ridge orientation angle θ which is computed in the previous section.

Hong et al. [7] proposed a method in which the fingerprint image is first divided into blocks of dimension $w \times w$. An oriented window of dimension $l \times w$ (33×17) is computed for each block centered at pixel (i, j) . This oriented window is used for getting X signature, $X[0], X[1] \dots X[l-1]$ of the ridge and valley, which is computed for each block centered at pixel (i, j) within an oriented window. Computation of X signature is based on the following expression.

$$X[k] = \frac{1}{w} \sum_{d=0}^{w-1} G(u, v) \quad (6)$$

$$u = i + (d - w/2) \cos \theta(i, j) + (k - l/2) \sin \theta(i, j) \quad (7)$$

$$v = j + (d - w/2) \sin \theta(i, j) + (l/2 - k) \cos \theta(i, j) \quad (8)$$

The frequency of the ridge and valley is estimated from the x -signature as the x -signature for each block forms a sinusoidal wave. Let the average number of pixel between the two consecutive peaks be $T(i, j)$. Then the frequency is defined as the reciprocal of $T(i, j)$ i.e. $F(i, j) = 1/T(i, j)$.

directions. Zhao et al. [5] computed the reliability from the If no consecutive peaks can be detected then a value of -1 is assigned to the frequency. This is done to differentiate it with the other valid blocks. No peaks can be obtained from the singular points, minutia or corrupted region of fingerprint. Thus the frequencies of these blocks are interpolated from the neighboring blocks using neighboring interpolation. For each block with the frequency value of -1 centered at (i, j) the interpolation is performed as follows:

$$F'(i, j) = \frac{\sum_{u=-w\Omega/2}^{w\Omega/2} \sum_{v=-w\Omega/2}^{w\Omega/2} W_g(u, v) \mu(F(i-uw, j-vw))}{\sum_{u=-w\Omega/2}^{w\Omega/2} \sum_{v=-w\Omega/2}^{w\Omega/2} W_g(u, v) \delta(F(i-uw, j-vw) + 1)} \quad (9)$$

where

$$\mu(x) = \begin{cases} 0 & x \leq 0 \\ x & \text{otherwise} \end{cases} \quad \delta(x) = \begin{cases} 0 & x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$

where W_g in Eq (9) is the Gaussian kernel of size $wg = 7$. The resultant value of f is interchanged with the F and the step is repeated for all the blocks of image. In order to remove the noise in F' a low pass filter can be used.

$$F(i, j) = \sum_{u=-wl/2}^{wl/2} \sum_{v=-wl/2}^{wl/2} W_l(u, v) F'(i-uw, j-vw) \quad (10)$$

Here W_l is a low pass filter with filter size of $wl = 7$.

V. Filtering

Filters are incorporated to get the ridge map used for removal of spurious pore that are not located on the fingerprint ridge. Gabor filter can be obtained by modulating a sinusoid of particular frequency and orientation with a Gaussian envelope. Gabor filter is a band pass filter which has both frequency selective and orientation selective properties. Thus by tuning the band pass filter to the corresponding frequency and orientation of sinusoidal wave of ridge and valley, the undesired noise can be removed resulting in a pure ridge valley structure. Gabor filter is used to extract the ridge valley structure. Hong at el. [7] used an even symmetric Gabor filter for the image enhancement which has the general form:

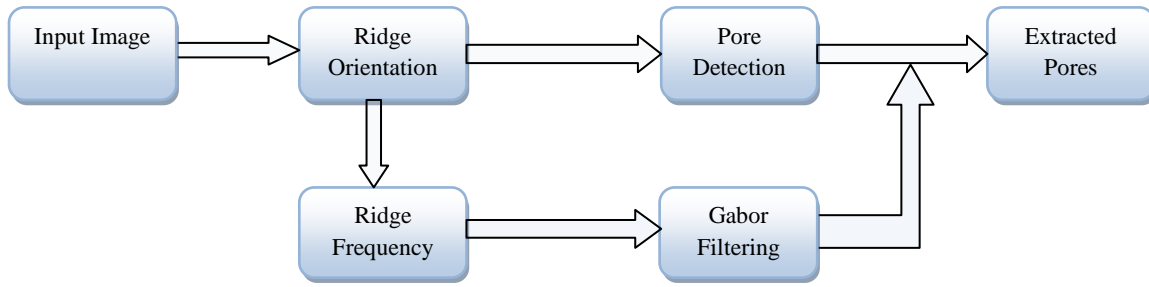


Fig 3: The Proposed Pore Extraction model

$$h(x, y: \theta, f) = \exp \left\{ -\frac{1}{2} \left[\frac{x_{\theta}^2}{\partial x^2} + \frac{y_{\theta}^2}{\partial y^2} \right] \right\} \cos (2\pi f x_{\theta}) \quad (11)$$

$$x_{\theta} = x \cdot \cos \theta + y \cdot \sin \theta \quad (12)$$

$$y_{\theta} = -x \cdot \sin \theta + y \cdot \cos \theta \quad (13)$$

Where ∂x and ∂y are the constants of the Gaussian envelope along x and y axes respectively. f is the frequency of the sinusoidal plane wave and θ is the orientation of the Gabor filter. The ridge orientation and ridge frequency parameters are determined in the previous sections. The standard deviations of the Gaussian envelope ∂x and ∂y has to be chosen carefully. For larger values of standard deviations filter will be robust to noise and will create more spurious ridge valley. On the other hand for smaller values filter will be less effective in removing noise and will create less spurious ridge valley.

VI. Anisotropic pore model

According to [9], open pores located on ridge and adjoining valley are anisotropic while closed pores are isotropic. The anisotropic pore model has a better pore detection efficiency irrespective of whether the pores are open or closed because along the orientation at pore, the intensity profile along the pore has a Gaussian shape. Jain et al. [10] used a Mexican hat wavelet transform to extract the pores in the fingerprint image with a constant scale factor. This constant scale factor is not suitable for a pore of varying size. Zhao et al. [5] proposed a dynamic anisotropic pore model which adaptively determines the scale and orientation parameter according to the local ridge features i.e. ridge orientation and

frequency. The dynamic anisotropic pore model is defined as follows:

$$\begin{cases} P_0(i, j) = e^{(-j^2/2\sigma^2)} \cos(\frac{\pi}{3\sigma} i) \\ -3\sigma \leq i, j \leq 3\sigma \end{cases} \quad (14)$$

$$\begin{cases} P_{\theta}(i, j) = Rot(P_0, \theta) = e^{(-\hat{j}^2/2\sigma^2)} \cos(\frac{\pi}{3\sigma} \hat{i}) \\ \hat{i} = i \cos(\theta) - j \sin(\theta), \hat{j} = i \sin(\theta) + j \cos(\theta) \\ -3\sigma \leq i, j \leq 3\sigma \end{cases} \quad (15)$$

Here Eq(14) is the reference model which models the pore located on horizontal ridges and Eq(15) is the rotated model which models the pore on ridges of orientation θ . The scale parameter σ determined from ridge frequency is used for pore size selection and θ is used to direct the pore model along the orientation. Here the scale parameter is set as a constant multiple of local ridge period. Zhao et al. [11] proposed a pore matched filter for pore detection based on the automatic scale selection technique. For more details on automatic scale selection please refer to [12].

VII. Pore extraction Algorithm

The overall method for reliably extracting pore is shown in Fig (3). The first stage is to compute the ridge orientation by dividing the image in a non-overlapping block (see Fig 4 (b)). In second stage the mean ridge frequencies on all the blocks are estimated (Fig 4 (c)). It then proceeds to the third stage where fingerprint image enhancement is done via bank of Gabor filters obtained from ridge orientation and frequency. The enhanced image is binaries and its complement is obtained resulting in a binary ridge map where the ridge pixels have value 1.

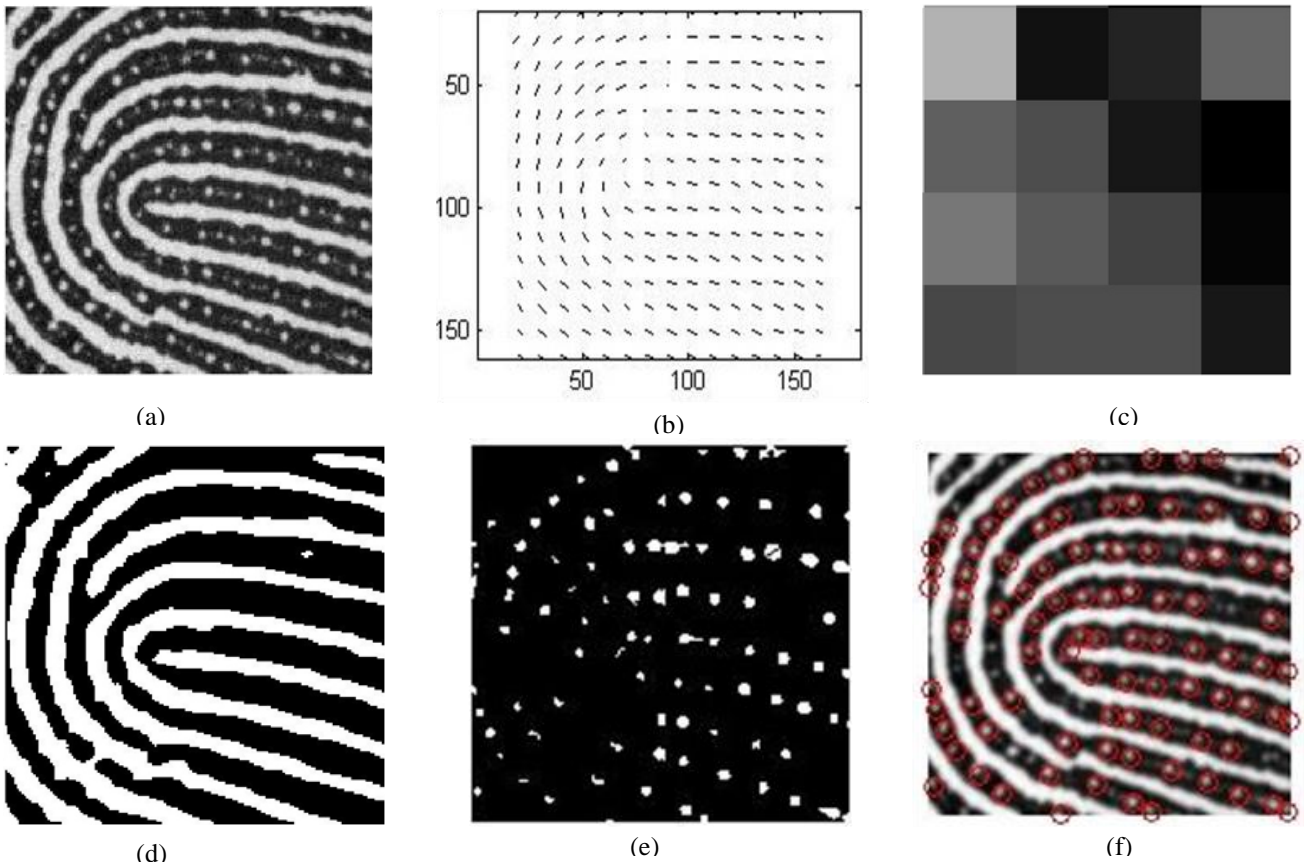


Fig 4.(a) is a fingerprint fragment, (b) is the ridge orientation of fragment in(a), (c) is the ridge frequency of fragment in (a), (d) is the Gabor filtered ridge map of fragment, (e) is the initial pore map and (f) shows the final detected pores in fingerprint fragment.

This ridge map (see Fig 4 (d)) is used to remove spurious pores during post processing. In the pore detection stage the proposed pore model is applied to the image blockwise followed by applying a threshold to the image so that the pore pixels have value 1 and non pore pixel have value 0. This resultant binary image is the pore map. (Fig 4 (e)).

As a post processing stage following steps were employed. First of all the pore map is filtered by the binary ridge map so as to remove the non ridge pixels. Then remove the pore pixels which have the least intensity. At last the connected components on the pore map are checked according to their size. The connected components having the number of pixels outside the pre-specified range (from 3 to 30 here) are removed from the pore map.

The final pore map obtained is shown in the Fig 4 (f).

VIII. Experimental Results

The purpose of fingerprint pore extraction algorithm is to model the spatial appearance of pores and improve the level of extraction of pores . Since pores are the fine detail on the fingerprint image it requires a sufficiently high resolution images for reliable extraction. The minimum resolution of image needed for extraction should be 1000 ppi.

The experiments were conducted on the high resolution partial fingerprint database PolyU High Resolution Fingerprint Database [6].The database (DBI) contains 1480 fingerprint images taken from 148 fingers and the image size

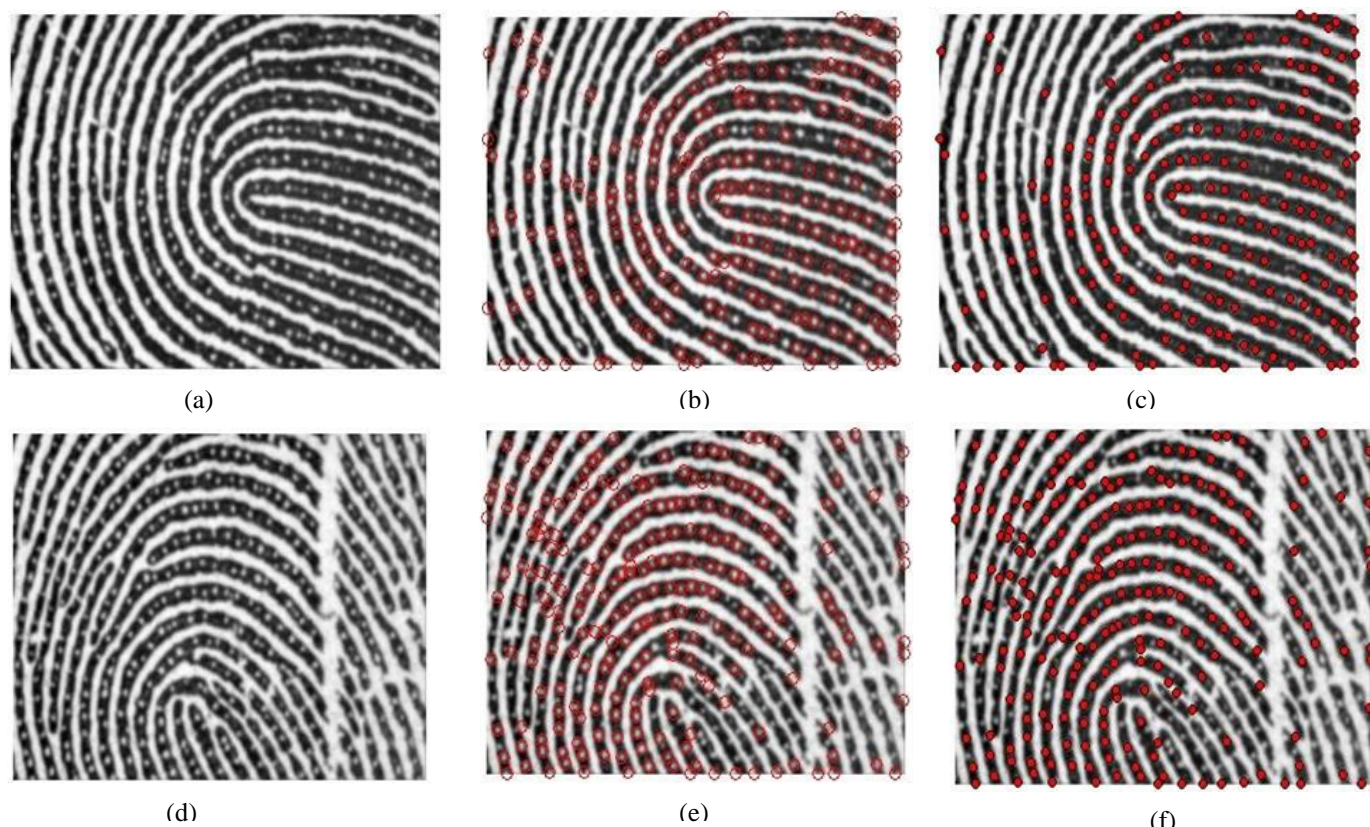


Fig 5. Examples of fingerprint pore extraction;(a) is a fingerprint fragment, (b) and (c) are the pore extraction results of (a), (d) is a fingerprint fragment, (e) and (f) are the pore extraction results of (d).

is 320 pixels in width and 240 pixels in height. The fingerprint image resolution is about 1200 ppi. Examples of the fingerprint pore extraction results are shown in Fig. 5. From these examples, we can see that our pore extraction algorithm has reliably extracted the more than sufficient pores required for pore matching.

IX. Conclusion

Here we have presented a dynamic anisotropic fingerprint pore model which detects the pores on the fingerprint images by using the adaptively obtained ridge orientation and ridge frequency. Pores on the fingerprint image were detected more accurately due to this adaptive nature of the pore extraction model. The images are enhanced using a set of Gabor filters tuned to corresponding frequency and orientation. This enhanced image is used for removing outliers from the pore map. The proposed pore extraction model is mainly used for the live scan fingerprint images.

References

- [1] A.K.Jain, P. Flynn, A.Ross, Handbook of Biometrics, Springer, 2007.
- [2] D. Maltoni, D. Maio, A.K. Jain, S. Prabhakar, "Handbook of Fingerprint Recognition", 2nd Edition, Springer-Verlag, 2009.
- [3] Asker M. Bazen, Sabih H. Gerez, "Systematic Methods for the Computation of the Directional fields and Singular points of Fingerprint", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, July 2002.
- [4] Nalini K. Ratha, Shaoyun Chen and A K. Jain, "Adaptive Flow Orientation Based Feature extraction In Fingerprint image, Pattern recognition, vol. 28, no. 11, pp. 1657-1672, 1995.
- [5] Qijun Zhao, David Zhang, Lei Zhang and Nan Luo, "Adaptive Fingerprint Pore Modeling and Extraction", Pattern Recognition, vol. 43(8), pp. 2833-2844, 2010.
- [6] "PolyU HRF Database, <http://www.comp.polyu.edu.hk/~biometrics/HRF/HRF.html>".
- [7] Hong, Y. Wan and A.K. Jain, "Fingerprint image enhancement: algorithms and

- performance evaluation," IEEE Trans. PAMI, Vol. 20, No. 8, pp.777-789, 1998.
- [8] NIST Special Database 27A, <http://www.nist.gov/itl/iad/ig/sd27a.cfm>
- [9] Qijun Zhao and Anil K. Jain, "On the Utility of Extended Fingerprint Features: A Study on Pores," *IEEE Computer Society Workshop on Biometrics*, CVPR2010, San Francisco, U.S., June 18, 2010.
- [10] A. K. Jain, Y. Chen, and M. Demirkus. Pores and ridges: Fingerprint matching using level 3 features, in Proceedings of ICPR06, vol.4, 2006, pp.477-480.
- [11] Q.Zhao, Jianjiang Feng and A.K.Jain," Latent Fingerprint Matching: Utility of Level 3 Features," MSU, Tech. Rep, MSU-CSE-10-14, August 2010.
- [12] T.Lindeberg, Edge detection and ridge detection with automatic scale section, *International Journal of Computer Vision* 30(1998)117-15.