DOI: 10.21917/ijivp.2017.0209

RELIABLE ORIENTATION FIELD ESTIMATION OF FINGERPRINT BASED ON ADAPTIVE NEIGHBORHOOD ANALYSIS

Shoba Dyre[1] and C.P. Sumathi[2]
Department of Computer Science, Shrimathi Devkunvar Nanalal Bhatt Vaishnav College for Women, India

Abstract
Fingerprint Orientation estimation is an important step in feature extraction and classification. However, a reliable extraction of fingerprint orientation data is still a challenge for poor quality images. In this paper, a gradient based estimation of orientation field based on the analysis of orientation consistency in the neighborhood for regularizing the orientation field is proposed. Experimental results are analyzed and compared with other existing gradient based methods used in this work. Evaluation performed on standard FVC2002 fingerprint databases DB1, DB2 and sample fingerprint images collected using optical fingerprint reader exhibit visibly better orientation estimation for various quality images using the proposed method.

Keywords:
Gradient-based Method, Orientation Map, Gaussian Filter, Orientation Smoothing, Orientation Consistency

1. INTRODUCTION

Among biometrical identity authentication systems, those based on fingerprint analysis are the most popular alternative for a large range of applications ranging from forensics to mobile phones. Fingerprint recognition system when properly implemented, provides a good balance of security, privacy, convenience and accountability [1]. A fingerprint is composed of a pattern of interleaved ridges and valleys [1]. The Fig.1 shows a fingerprint image scanned by an optical scanner.

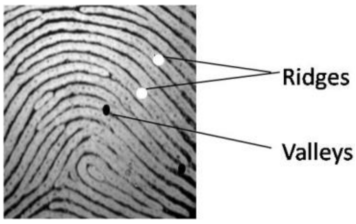


Fig.1. Ridges and Valleys in a fingerprint image

Though extensive research have been done over the past few decades, there are still a number of challenges in designing reliable algorithms for fingerprint authentication, due to the large intra-class variability and large inter-class similarity in fingerprint patterns. A feature extraction stage for identifying salient features is employed by most of the fingerprint authentication systems. Fingerprint features are classified as local and global. As a most significant global feature, fingerprint orientation field describes the directionality of local ridge structure of a fingerprint and provides rich information for most of the successive feature extraction and classification steps. New methods for computation of orientation map (OM) are desirable especially for low quality images.

Over the past two decades, different approaches have been applied to estimate orientation field (OF) of fingerprint patterns such as gradient method, Slit and projection based approaches, Gray-level consistency/variance method and estimations in the frequency domain [15]. Among all the methods, gradient squared averaging method is widely used to compute the orientation field of an image block because of its high efficiency and resolution [9][10][11][16][18][19]. Gradient extraction is sensitive to noise and imperfections and therefore OM estimation may not be reliable [14]. However, this problem can be solved by an orientation smoothing stage to obtain a better representation of the ridge structure for fingerprint classification.

In this work, existing approaches for fingerprint orientation extraction available in the literature have been reviewed, and a gradient based method is proposed for obtaining a reliable fingerprint orientation field estimate. It is based on a regularization approach that adaptively changes the smoothing neighborhood size after analyzing the orientation consistency of neighboring blocks [2]. Noise in the orientation estimation of poor quality fingerprint images is attenuated and further improved by applying a Gaussian function during the smoothing stage. The sine and cosine part of the doubled angle representation is convolved with a low pass Gaussian kernel of adaptive size. Experimental results of the proposed method exhibit reliable orientation field for noisy areas while preserving high curvature areas around singular points than the gradient based methods used in this work [2][8] and [13] for comparative analysis.

A review of previous approaches for fingerprint orientation field estimation is presented in section 2. Section 3 provides an overview of Gradient based method for orientation estimation. The proposed gradient-based adaptive neighborhood smoothing approach for estimating reliable orientation field is given in section 4. Experimental results conducted on a set of fingerprints in order to evaluate the proposed method are presented in section 5. Section 6 concludes the paper.

2. RELATED WORK

Many approaches to estimation of orientation field have been presented in the literature and the most widely used are gradient based [2] [8] [9] [11] [12] [16] [18] [19], slit based and Fourier analysis.

Slit based approaches analyze the intensity variances along a set of orientations and choose the most probable orientation based on pixel gray-values along the slits [4]. The standard deviation of the gray scale intensities corresponding to each slit is computed in the method proposed in [20] and the optimal slit is selected according to the maximum standard deviation contrast between a slit and its orthogonal slit [1]. Computational complexity of slit based method is high and quantization might produce a coarser angular resolution[1].

Orientation estimation based on Short Time Fourier

Transform analysis proposed in [17] divided the image into partially overlapped blocks and Fourier Transform is computed. The probability of the orientation value θ within the block is then computed as the marginal density function [17]. A more robust orientation smoothing algorithm is needed for reliable estimation [17].

A gradient based fingerprint orientation field estimation algorithm based on optimized neighborhood averaging is presented in [11]. A look-up table is used to analyze blocks in the neighboring regions for smoothing the OF. The computational complexity is high and look up table creates overhead.

An algorithm for estimating the orientation field for general flow-like texture images was proposed in [8]. A new measure of coherence for computing the reliability of estimated orientation was also proposed by them. The orientation field estimation for fingerprint images was not satisfactory.

A gradient based approach that adopts an adaptive orientation smoothing neighborhood size was proposed in [2]. The window size of 5×5 for orientation estimation is used in the present system that exhibits high sensitivity to noise.

A novel principal compound analysis (PCA) based gradient approach was proposed as in [10] to estimate the directional field from fingerprints. Coherence algorithm calculated using the squared gradient method was used for segmenting the fingerprint. However, this does not contribute to obtain a reliable orientation estimation of fingerprints.

3. GRADIENT BASED METHOD - AN OVERVIEW

The fingerprint orientation image is a two-dimensional matrix whose elements encode the local orientation of the fingerprint ridges $\{\theta_{xy}\}$ where, $\theta_{xy} \in [0, \pi]$. The gradient phase angle, point to the direction of highest variation of gray intensity which is orthogonal to the direction of the edge of ridge lines θ. The components of the gradient G_x and G_y can be determined using the classical Prewitt or Sobel convolution masks. The gradient vector in the Cartesian coordinate $[G_x, G_y]^T$ for an image I is denoted as

$$\begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \dfrac{\delta_I}{\delta_x} \\ \dfrac{\delta_I}{\delta_y} \end{bmatrix} \tag{1}$$

The θ can be computed as the arctangent of G_y/G_x. This presents problem due to non-linearity and discontinuity around 90^0 Also if for each (x,y), the orientation is estimated in the image, it reflects the ridge-valley orientation at too fine a scale and therefore it is too sensitive to noise in the fingerprint image.

So to solve this problem, Kas and Witkin [13] proposed a solution to the above mentioned problem which allows local gradient estimate to be averaged in a non-overlapping block specified by a window size W. As opposite gradients at both sides of a ridge line is likely to cancel each other, gradients cannot be simply averaged in the local neighborhood. The basic idea is to double the gradient angles before the averaging process so that $(\theta + \pi)$ becomes $(2\theta + 2\pi)$ which is equal to 2θ. The gradient vector is converted to the polar system for the purpose of doubling the angle. This is denoted as

$$\begin{bmatrix} g \\ \theta \end{bmatrix} = \begin{bmatrix} \sqrt{G_x^2 + G_x^2} \\ \tan^{-1}\left[\dfrac{G_x}{G_y}\right] \end{bmatrix} \tag{2}$$

The gradient vector converted back to its Cartesian is represented by,

$$\begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} g\cos\theta \\ g\sin\theta \end{bmatrix}$$

An expression for the squared gradient vectors $[G_{sx}, G_{sy}]^T$ that do not make use of g and θ is found using trigonometric identities as

$$\begin{bmatrix} G_{sx} \\ G_{sy} \end{bmatrix} = \begin{bmatrix} g^2\cos 2\theta \\ g^2\sin 2\theta \end{bmatrix} = \begin{bmatrix} g^2\left(\cos^2\theta - \sin^2\theta\right) \\ g^2\left(2\sin\theta\cos\theta\right) \end{bmatrix} = \begin{bmatrix} G_x^2 - G_y^2 \\ 2G_xG_y \end{bmatrix} \tag{3}$$

The averaged squared gradient in a block specified by a window size W can be calculated by,

$$\begin{bmatrix} \bar{G}_{sx} \\ \bar{G}_{sy} \end{bmatrix} = \begin{bmatrix} \sum_W G_{sx} \\ \sum_W G_{sy} \end{bmatrix} = \begin{bmatrix} \sum_W G_x^2 - G_y^2 \\ \sum_W 2G_xG_y \end{bmatrix} = \begin{bmatrix} G_{xx} - G_{yy} \\ 2G_{xy} \end{bmatrix} \tag{4}$$

where

$$G_{xx} = \sum_W G_x^2$$

$$G_{yy} = \sum_W G_y^2$$

$$G_{xy} = \sum_W G_xG_y$$

These are the estimates for the covariance and cross covariance of G_x and G_y.

The direction of orientation field for a block B of size $W\times W$ that is perpendicular to the gradient direction is given by

$$\theta_B = \frac{1}{2}\tan^{-1}\left(\frac{\sum_{i=1}^{W}\sum_{j=1}^{W}\left(2G_x(i,j)G_y(i,j)\right)}{\sum_{i=1}^{W}\sum_{j=1}^{W}\left(G_x^2(i,j) - G_y^2(i,j)\right)}\right) + \frac{\pi}{2} \tag{5}$$

A metric called coherence was introduced in [13] to measure the reliability of orientation estimation θ of a block to determine the strength of the averaged gradient in the distribution of local gradient vectors. Coherence of a block is given by [13].

$$Coh_B = \frac{\left|\sum_{i=1}^{W}\sum_{j=1}^{W} G_{sx}(i,j), G_{sy}(i,j)\right|}{\sum_{i=1}^{W}\sum_{j=1}^{W}\left|G_{sx}(i,j), G_{sy}(i,j)\right|} \tag{6}$$

4. PROPOSED RELIABLE ORIENTATION FIELD ESTIMATION

For low quality regions in fingerprints, extracting reliable orientation field is still an open problem [5] As computational complexity of other existing approaches is usually higher than gradient-based techniques, an approach for extracting Ridge orientation based on gradient squared averaging method is used [19] because of its high efficiency and resolution. This coarse representation is unreliable for poor quality fingerprints with cuts and creases for further processing. To overcome the undesired effects and make it more reliable, we require an orientation regularization algorithm. Hence, we propose a method that adopts an adaptive orientation smoothing neighborhood size as proposed in [2] based on analysis of the orientation consistency, but have improved the DF estimate with convolution of a low pass Gaussian kernel of adaptive size. It gives a better estimate for poor quality images than the method proposed in [2]. The stages for processing are shown in Fig.2 and they are explained in detail below:

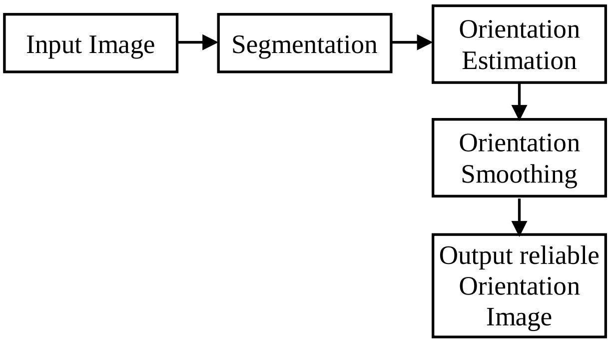


Fig.2. Steps necessary for reliable Orientation estimation

4.1 SEGMENTATION BASED ON VARIANCE THRESHOLDING

The fingerprint image consists of a region of interest (ridges and valleys of fingerprint impressions). To avoid extraction of features in noisy and background areas of the fingerprint we need to segment the fingerprint area. Background regions exhibit a very low gray-scale variance value and foreground regions have a very high variance. Mean and variance based method for segmenting the fingerprint area [9] is used in this work. The gray scale variance is calculated for each non overlapping block in the fingerprint image and if the variance is less than the global threshold, then the block is assigned as background. A block size of 8×8 is used.

The mean and variance of the block $W\times W$ in the fingerprint image I is given by,

$$M(I)=\frac{1}{W^2}\sum_{i=0}^{W-1}\sum_{j=0}^{W-1} I(i,j) \tag{7}$$

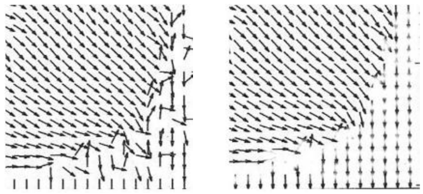
$$VAR(I)=\frac{1}{W^2}\sum_{i=0}^{W-1}\sum_{j=0}^{W-1}\left(I(i,j)-M(I)\right)^2 \tag{8}$$

Only the blocks above the threshold variance is considered for further processing. The global threshold variance has been chosen to be 100. The Fig.3 shows the segmented fingerprint image.

(a) (b)

Fig.3. (a) Original image (b) Fingerprint foreground region after segmentation

Without segmentation, the directional field is computed for noisy areas in the background outside the fingerprint region as shown in Fig.4 that may lead to false extraction of features for further processing.



(a) (b)

Fig.4. Orientation estimation (a) without segmentation (b) after segmentation

4.2 ORIENTATION ESTIMATION

The dominant orientation of an image block is estimated by the least square method based on the gradients because of its high efficiency. The steps are as follows:

Step 1: Divide the fingerprint image into non overlapping blocks of size $W\times W$ pixels. The size of the block should be sufficient enough to be able to obtain a good estimate of the local ridge flow and cannot be too large as the changes in the local orientations need to be captured in order to locate the global characteristics of the fingerprints. The block size of W=8 is used for estimating block orientation in this work as the average width of the ridges are 5 to 8 pixels.

Step 2: Compute the gradients G_x and G_y of each pixel with respect to the horizontal and vertical directions respectively. The Sobel convolution mask is used in this work to determine the components of the gradient.

Step 3: Estimate the local orientation field of the block by gradient squared averaging using the Eq.(4) and Eq.(5). The orientation field serves to decide the pattern class of the input fingerprint image.

4.3 ORIENTATION SMOOTHING

The orientation image computed from poor quality fingerprints may contain several unreliable elements due to creases, local scratches or cluttered noise. The estimate will also be inaccurate when the frame consists entirely of uncovered regions with poor ridge structure or poor ridge contrast. The Fig.5 shows the unreliable directional field computed for such a region using subsection 4.2.

Hence, the orientation smoothing stage is implemented to compute a reliable directional image. The smoothing method based on doubling the orientation estimate and averaging the angles in a local fixed $n \times n$ window has some limitations in smoothing noisy region as noise may be heavy or light. This method also negatively smoothen the high curvature area when the window size is too large and heavy noise cannot be well attenuated if the window size is too small. The method proposed in [2] noted that reliable local ridge orientation field is consistent except for high curvature areas or noisy areas as shown in Fig.6. The difference between high curvature and noisy areas is that the orientation consistency improves with increasing neighborhood size for noisy regions, but is always lower than a threshold for high curvature areas. Orientation consistency describes how well the orientations over a neighborhood are consistent with the dominant directions [2].

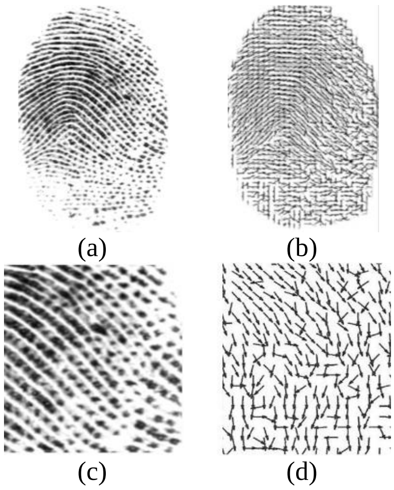


Fig.5. (a) Low-quality original fingerprint image from Db1 database, (b) overlaid unreliable orientation on the image, (c) and (d) segment of the noisy area and its DF estimated using section 4.2

The orientation smoothing used in this work is based on the estimated measure of coherence as proposed in [8]. This measure is based on gradient magnitude G and orientation estimation. The coherence for a point (x_0,y_0) is defined as:

$$OC(s) = G(x_0,y_0)\frac{\sum_{(i,j\in w(s))}\left\|G(x_i,y_i)\cos\left(\theta(x_0,y_0)-\theta(x_i,y_i)\right)\right\|}{\sum_{(i,j\in w(s))}G(x_i,y_i)} \quad (9)$$

where, $w(s)$ is the neighborhood of each block to be considered. The orientation consistency $OC(s)$ ranges from 0 and 1. It gives a highest value of 1 if all the orientations in $w(s)$ is directed in the same direction and approaches 0 when orientation discordance increases.

To decide on the size of the smoothing neighborhood for a block, the orientation consistency is evaluated based on the outside surrounding blocks of $(2s+1)\times(2s+1)$ consisting of $8\times s$ elements starting with $s = 1$ to a maximum neighborhood size of 4 (used in this work). After determining the smoothing size, a low pass Gaussian kernel of size $(2s+1)\times(2s+1)$ is convolved with the neighborhood of the block. The 2-D Gaussian function is given by,

$$g(x,y) = \frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (10)$$

where, x and y are the distances in blocks in the horizontal and vertical directions from the central block $\theta(i,j)$ and σ determines the scale of the Gaussian function. The processing step of the proposed orientation smoothing method is given below and summarized using flowchart in Fig.7.

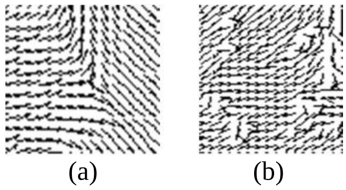


Fig.6. Orientation field where consistency is low (a) High curvature region (b) Noisy region

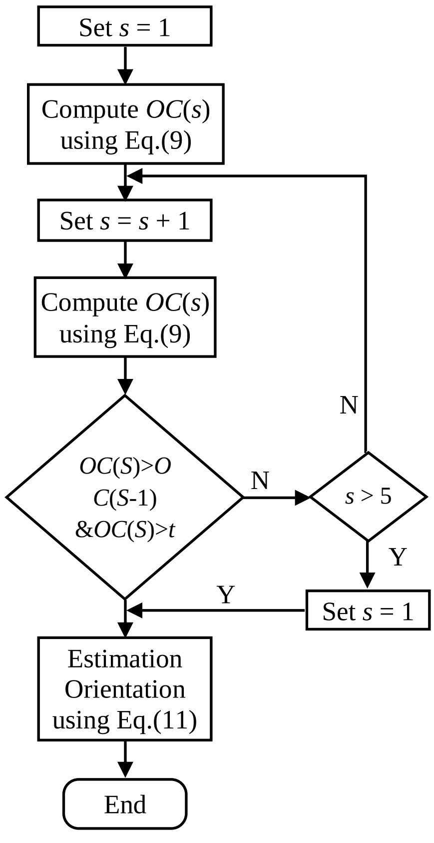


Fig.7. Processing flowchart of the proposed orientation smoothing method

Step 1: Initially set $s = 1$ and maximum value of s to be 5. Convert the orientation θ of each block to vector fields $\varphi_x = \cos 2\theta$, $\varphi_y = \sin 2\theta$

Step 2: Compute the orientation coherence using Eq.(9) where $w(s)$ are the outside blocks of its $(2s+1)\times(2s+1)$ neighborhood.

Step 3: Set $s=s+1$ and compute the orientation coherence using Eq.(9).

Step 4: If the orientation consistency is greater than a threshold

(0.3 in our work) and also greater than $OC(s\text{-}1)$, go to step 6, otherwise go to step 3 if s is smaller than the maximum value of 4.

Step 5: Set $s = 1$

Step 6: Gaussian smoothing is performed on the vector fields

$$\varphi_x' = \sum G * \varphi_x$$
$$\varphi_y' = \sum G * \varphi_y$$

where, the summation is taken over the local adaptive smoothing neighborhood size $(2s+1)\times(2s+1)$, G represents a Gaussian low pass kernel of adaptive size $(2s+1)\times(2s+1)$.

Step 7: The final smoothed orientation θ is given as:

$$\theta' = \frac{1}{2}\tan^{-1}\frac{\varphi_y'}{\varphi_x'}$$

If the orientation consistency is smaller than the threshold and s reaches its maximum value, the smoothing neighborhood $w(s)$ is most likely a high curvature area.

5. EXPERIMENTAL RESULTS AND EVALUATION

This section reports some experimental results obtained by the proposed orientation smoothing method and compares it with other orientation smoothing approaches. Experiments were conducted on three sets of fingerprints. The first two sets are standard FVC2002 fingerprint databases DB1 and DB2. The images' size of Db1 is 640×480 pixels, Db2 is 328×364. Third set contains fingerprint images collected from heterogeneous population that includes manual workers and people from different age groups using an optical Fingerprint Reader. The size of each image is 480×320 pixels. There is variation in these sets of fingerprints in quality and type. All these are 256 gray-level images.

For the purpose of comparison, three previous gradient-based approaches: the conventional smoothing method using fixed size Gaussian envelop as proposed in [13], non-adaptive smoothing based on the orientation coherence estimation as presented in [8] an adaptive smoothing neighborhood approach in [2] and the proposed method were implemented in MATLAB and analyzed on the above mentioned data sets. A block size of 5×5 as proposed in [2] for Orientation estimation shows high sensitivity to noise in the images. Hence, in this work, a block size of 8×8 is used to estimate orientation field, as the average width of ridges are 5 to 9.

As the orientation field estimated using gradient squared averaging method is unreliable for further processing as shown in Fig.5, the orientation smoothing stage is implemented. The orientation extracted using the three gradient-based approaches [13][2][8] and the proposed method were compared in noisy region of very poor quality fingerprints. In high curvature areas, the OF estimation proposed in [2] with window size 8×8, and the proposed method exhibit similar results as shown in Fig.9, the method [13] excessively smoothen the high curvature area. In very noisy region as shown in Fig.8, the estimation is unreliable even after regularization using the methods proposed in [13] and [8]. For medium and good quality image segments the method proposed in [13] using fixed size Gaussian kernel gives good orientation estimation. The proposed adaptive neighborhood smoothing method visibly attenuate noise better than other approaches as shown in Fig.8, and also preserve high curvature areas around singular points.

The Fig.10 displays the segments of fingerprint images of various qualities of the same fingerprint around the core point. The Signal-to-Noise Ratio (SNR) measure in decibels (DB) is used to estimate the input fingerprint image quality. It is given by $10\log_{10}$ (mean of pixel values/standard deviation of pixel values). Images with lower SNR values have scars, cuts and creases that show discontinuity in the ridges. Good quality images have higher SNR values. These examples also exhibit better OF estimate using the proposed adaptive neighborhood analysis approach by preserving the directionality of the ridge structure.

For fingerprint images of various qualities and types shown in Fig.11(a), the estimated orientation field overlaid on these images using the proposed method is shown in Fig.11(b). The orientation coherence estimate used in this work as proposed in [8] yields better results as it places more weight on regions that have higher visual contrast.

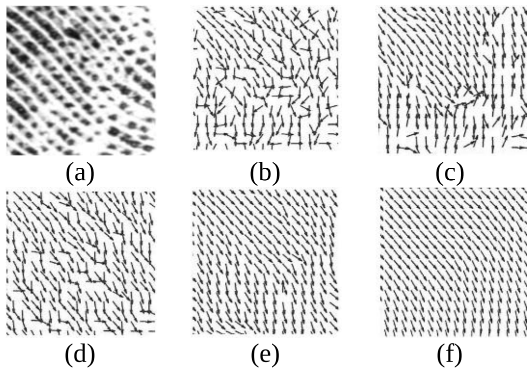


Fig.8. (a) Original noisy fingerprint segment, (b) Before orientation smoothing, (c) Smoothing using conventional averaging method [13] (d) OF as proposed in [8] (e) Adaptive Smoothing method proposed in [2]with 8×8 window (f) Proposed adaptive smoothing method

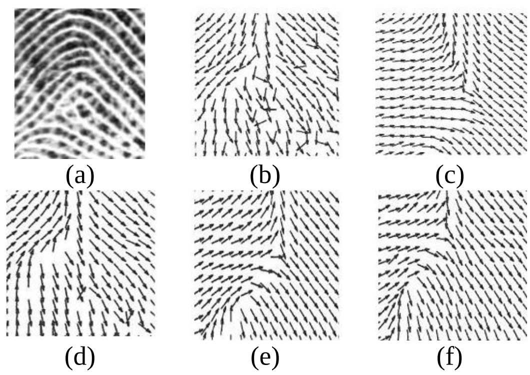


Fig.9. (a) Original high curvature area in noisy fingerprint, (b) Before orientation smoothing (c) non adaptive averaging method [13] (d) method as in [8] (e) Adaptive Smoothing method proposed in [2] using 8×8 window size (f) Proposed adaptive smoothing method

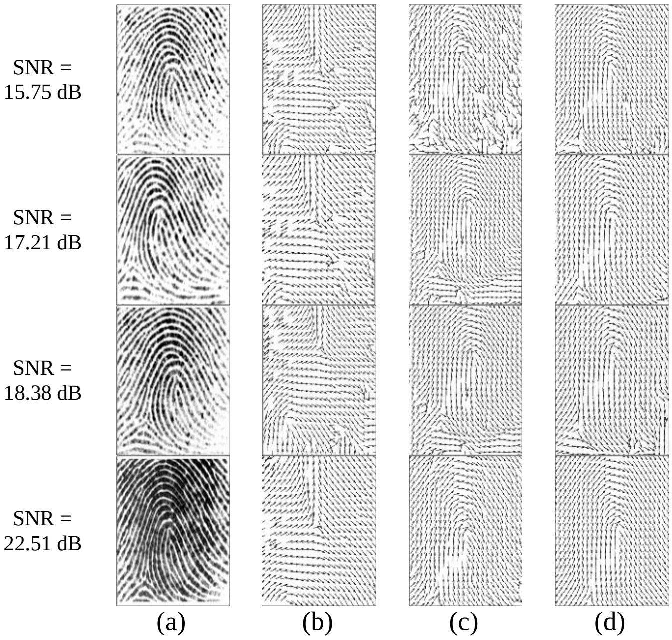


Fig.11. (a) Fingerprint images of various quality and type with noise, cuts and creases (b) their respective estimated orientation field superimposed on the images using the proposed method

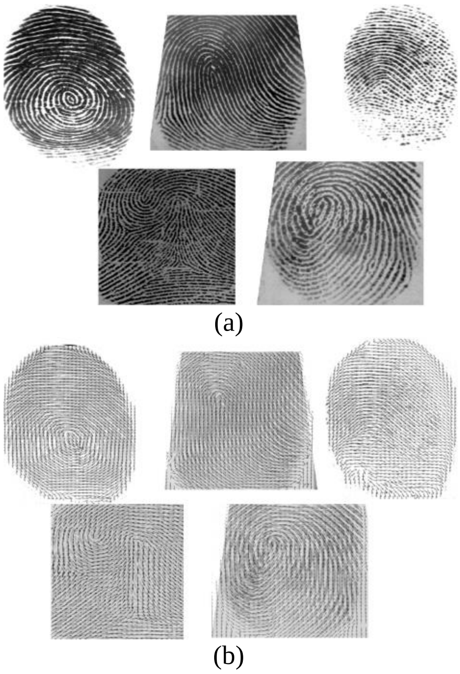


Fig.10. (a) segments of fingerprint images of various qualities /SNR values of the same fingerprint around the core point and their OF estimate using (b) non-adaptive averaging method [13] (c) Adaptive Smoothing method proposed in [2] using 8×8 window size (d) Proposed adaptive smoothing method

6. CONCLUSION

Local ridge orientation estimation is an important step in fingerprint image processing. Hence a reliable orientation estimate is vital in fingerprint feature extraction, classification and recognition. In fingerprint areas of low quality, the orientation image extraction is still a challenging task and most existing approaches to the computation result in poor estimate.

A reliable method based on adaptive neighborhood smoothing for fingerprint orientation image estimation was proposed. Experimental results conducted on a collection of fingerprints demonstrate that the proposed method is robust to noise and exhibit visibly better orientation estimates compared with the previous adaptive and non-adaptive gradient based approaches and also preserve high curvature regions. The estimated orientation field is used for extracting singular points in fingerprints**.**

REFERENCES

[1] Davide Maltoni, Dario Maio, Anil K.Jain and Salil Prabhakar, "*Handbook of Fingerprint Recognition*", 2nd Edition, Springer, 2009.

[2] Manhua Liu, Xudong Jiang and Alex Chichung Kot, "Fingerprint Reference-Point Detection", *EURASIP Journal on Applied Signal Processing*, Vol. 4, pp. 498-509, 2005.

[3] Jinwei Gu, Jie Zhou and David Zhang, "A Combination Model for Orientation Field of Fingerprints", *Pattern Recognition*, Vol. 37, No. 3, pp. 543-553, 2004.

[4] Xiao Yang, Jianjiang Feng and Jie Zhou, "Localized Dictionaries Based Orientation Field Estimation for Latent Fingerprints", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 36, No. 5, pp. 955-969, 2014.

[5] Francesco Turroni, Davide Maltoni, Raffaele Cappelli and Dario Maio, "Improving Fingerprint Orientation Extraction", *IEEE Transactions on Information Forensics And Security*, Vol. 6, No. 3, pp. 1002-1013, 2011.

[6] Iwasokun Gabriel Babatunde, Akinyokun Oluwole Charles and Olabode Olatubosun, "A Block Processing Approach to Fingerprint Ridge-Orientation Estimation", *Computer Technology and Application*, Vol. 3, pp. 401-407, 2012.

[7] Jayant V. Kulkarni, Bhushan D. Patil and Raghunath S. Holambe, "Orientation Feature for Fingerprint Matching", *Pattern Recognition*, Vol. 39, No. 8, pp. 1551-1554, 2006.

[8] Ravishankar Rao and Brian G. Schunck, "Computing Oriented Texture Fields", *Graphical Models and Image Processing*, Vol. 53, No. 2, pp. 157-185, 1991.

[9] Nalini K. Ratha, Shaoyun Chen and Anil K. Jain, "Adaptive Flow Orientation-Based Feature Extraction in Fingerprint Images", *Pattern Recognition*, Vol. 28, No. 11, pp. 1657-1672, 1995.

[10] Asker M. Bazen and Sabih H. Gerez, "Systematic Methods for the Computation of the Directional Fields and Singular Points of Fingerprints", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 24, No. 7, pp. 905-919, 2002.

[11] H.B Kekre and V.A Bharadi, "Fingerprint Orientation Field Estimation Algorithm based on Optimized Neighborhood Averaging", *Proceedings of 2ndInternational Conference on Emerging Trends in Engineering and* Technology, pp. 228-234, 2009.

[12] Manhua Liu, Xudong Jiang and Alex Chichung Kot, "Nonlinear Fingerprint Orientation Smoothing by Median Filter", *Proceedings of International Conference on Information Communications and Signal Processing*, pp. 1439-1443, 2005.

[13] Michael Kaas and Andrew Witkin, "Analyzing Oriented pattern", *Computer Vision, Graphics, and Image* Processing, Vol. 37, No. 3, pp. 362-385, 1987.

[14] Mikel Galar et al., "A Survey of Fingerprint Classification Part II: Experimental Analysis and Ensemble Proposal", *Knowledge-Based Systems*, Vol. 81, pp. 98-116, 2015.

[15] R. Cappelli, A. Lumini, D. Maio and D. Maltoni, "Fingerprint Classification by Directional Image Partitioning", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 21, No. 5, pp. 402-421, 1999.

[16] Lukasz Wieclaw, "Gradient Based Fingerprint Orientation Field Estimation", *Journal of Medical Informatics and Technologies*, Vol. 22, pp. 202-207, 2013.

[17] Sharat Chikkerur, Alexander N. Cartwright and Venu Govindaraju, "Fingerprint Enhancement using STFT Analysis", *Pattern Recognition*, Vol. 40, No. 1, pp. 198-211, 2007.

[18] Yi Wang, Jiankun Hu and Fengling Han, "Enhanced Gradient-based Algorithm for the Estimation of Fingerprint Orientation Fields", *Applied Mathematics and Computation*, Vol. 185, No. 1, pp. 823-833, 2007.

[19] Asker M. Bazen and Sabih H. Gerez, "Directional Field Computation for Fingerprints Based on the Principal Component Analysis of Local Gradients", *Proceedings on Workshop on Circuits, Systems and Signal Processing*, pp. 1-7, 2000.

[20] M.A. Oliveira and N.J. Leite, "A Multiscale Directional Operator and Morphological Tools for Reconnecting Broken Ridges in Fingerprint Images", *Pattern Recognition*, Vol. 41, No. 1, pp. 367-377, 2008.