Quality Assessment Based Fingerprint Segmentation

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Abstract. Lack of robust segmentation against degraded quality image is one of the open issues in fingerprint segmentation. Good fingerprint segmentation effectively reduces the processing time in automatic fingerprint recognition systems. Poor segmentation result in spurious and missing features thus degrading performance of overall system. Segmentation will be more effective if done in accordance to the quality of image. Fingerprint images with high quality have wide range of features which can be used for segmentation than the low quality image, where the fingerprint features are not clearly visible. This paper focus on the two folded segmentation process comprising of quality evaluation and segmentation based on it. Various global and local features are used for assessing quality of image and thereby using them for segmenting ridge area from plain background. The segmented images are compared using percentage of foreground area to total area, genuine number of minutiae points extracted from segmented area. The time taken for image segmentation is also used as a performance parameter. The proposed approach has been tested with images of different qualities from NIST and FVC data sets and the results are proven to be better than the conventional segmentation approaches.

Keywords: OCL (Orientation Certainty Level), Quality Index, CM (Consistency Measure).

1 Introduction

Fingerprint segmentation is one of the first and most integral pre processing steps for any fingerprint verification/identification system. With the onset of the use of fingerprint recognition at large scale, there is rising demand to increase the reliability of fingerprint identification in non ideal conditions. A captured fingerprint image usually consists of two components-foreground region and background region .The poor quality images pose difficulty in detecting features from the image and hence may decrease the recognition performance. The aim of fingerprint segmentation is to identify and exclude un-interested regions and unrecoverable poor quality fuzzy regions from

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the captured fingerprint image and keeps ridge area as foreground. After segmentation subsequent processing will be focused only on foreground of fingerprint image.

Effective fingerprint segmentation can not only reduce the computation amount for post processing steps in the system, but also improve the reliability of extracted features notably [1]. Fingerprint image is segmented according to different features between ridge area and non ridge area. Previous studies demonstrate that the performance of a fingerprint recognition system is heavily affected by the quality of fingerprint images [6], [7]. A number of factors can affect the quality of fingerprint images [11]: occupation, motivation/collaboration of users, age, temporal or permanent cuts, dryness/wetness conditions, temperature, dirt, residual prints on the sensor surface, etc. Unfortunately, many of these factors cannot be controlled and/or avoided. For this reason, assessing the quality of captured fingerprints is important for a fingerprint recognition system. When fingerprint images include a noisy background, feature extraction algorithms extract a lot of false features.

In this paper, segmentation is based on the quality estimation from the multiple features (local and global features both) captured from fingerprint image. In section 2 the proposed algorithm is illustrated. Proposed algorithm consists of four phases: Pre-processing phase, Computing Quality index from various features, adaptive segmentation in accordance to the quality index is applied and finally post processing phase is applied to merge the isolated blocks. Pre-processing phase consists of application of Gaussian filter to weaken the noise effect captured from the sensor surface and quality estimation based on direction field is done. According to quality index of the input fingerprint image three approaches are used. For good quality index, dominant ridge score and orientation certainty level is used for segmentation .For average quality input image, the adaptive gradient variance approach is combined with consistency measure of fingerprint is used for segmentation .To increase the segmentation reliability for low quality images gradient based segmentation is used to approximate the foreground region of fingerprint images along with orientation reliability score. After the segmentation stage, post processing is done by taking into consideration the continuity of ridges in the neighboring blocks. The experimental results based on proposed method is displayed in section 4 and in section 5, the conclusion is presented.

2 Methodology: Problem Formulation and Proposed Approach

The problem considered here is to extract foreground region from fingerprint image. For good quality image, a simple technique of tracing flow of ridges is enough to segmentation. In average or poor quality images the orientation flow is smudged by noise or some other factor, so tracing ridge flow alone may result in improper segmentation. For segmentation of poor quality image where ridges are corrupted over fairly large portion of captured area, the reliability of orientation flow analysis needs to be assured before segmentation.

The philosophy of the presented quality assessment based segmentation scheme lies in its multidimensional approach of analyzing and estimating quality indices of the fingerprint images. This multilayered technique acquires varied estimation factors, providing a broad base to the quality assessment system thereby improving segmentation robustness. The techniques in this arrangement complement each other, while minimizing their individual weaknesses and reinforcing the overall system strength. The approach consists of:

2.1 Preprocessing

The image pre-processing process consists of image normalization [3] and Gaussian smoothing. We used normalization to normalize the gray-level variations. After that, a 5x5 Gaussian filter was applied to reduce the amount of noise in the image.

2.2 Image Quality Assessment Using Multi-level Factors

First of all, we consider which factors are important when a person evaluate the quality of a fingerprint image using human visual system, which can help us establish better evaluation system. It's obviously that the first impression is whether the foreground of the fingerprint image can supply the enough information. So the size of foreground is very important for image quality assessment. Second, viewers would use some global features to judge, such as image contrast and frequency information, which reflect the image quality basically. And then, viewers need to watch the images carefully on purpose. And they would mostly likely to watch structure of ridge lines .If all these factors have better performance, the image will have better quality.

2.2.1 Effective Area Estimation

Quality assessment process is initiated by the foreground area calculation, which is defined as the percentage of the foreground blocks to the total area [19].A smaller value of effective area would mean a smaller area of fingerprint has been captured. Image requires re-capturing if the effective area value is less than set threshold value.

2.2.2 Main Energy Ratio

Because of noise, we define main energy ratio as:

$$\text{Main Energy Ratio}= \frac{Ep1+Ep2}{E-(Ep1+Ep2)} \tag{1}$$

Where $E=\sum F(i,j)$, if $F(i,j) > E_{p1} \times 30\%$

Where $F(i,j)$ is the value of image in the frequency domain after FFT, s is a circle with radius of r, r is the distance from the peak to the DC component and is round to the nearest integer. Ep1 is the value of one peak. Ep2 is the value of the other peak. Ep1 is approximately equal to Ep2. The quality values for the low- and high-quality image are 0.35 and 0.88, respectively.

2.2.3 Image Contrast

Image contrast can be defined as the normalization of variance. Two options for the image contrast are available: Michelson Contrast, Weber Contrast [20].

2.2.4 Consistency Measure

To measure the consistency of the image, firstly the 255 gray levels image are changed into binary image. Secondly, the 3*3 neighbourhood is used, whose centre moved from pixel (2,2) to (255,255), to measure the consistency of ridge flow lines. Following equations are used to determine consistency and consistency measure:

$$\text{consistency}(i,j) = \begin{cases} 0.2 * \text{cen}(i,j) * (9 - \text{sum}(i,j)) + \text{cen}(i,j), 4 < sum(i,j) < 9 \\ (1 - \text{cen}(i,j)) + (0.2 * \text{sum}(i,j) * \text{cen}(i,j)), \text{sum}(i,j) \leq 4 \end{cases} \tag{2}$$

$$\text{Consistency measure} = \sum_{i=2}^{r-1}\sum_{j=2}^{c-1} \text{consistency}(i,j) \tag{3}$$

Where cen(i,j) being the value of the pixel (i,j), sum(i,j)is the summation of values of 3*3 neighbourhood cantered at pixel (i,j),r & c be the rows and columns present in image.

Rule based system for calculating Quality Index using multiple parameters extracted from global analysis and local analysis of image:

If (Aeff and Contrast > Th1) then
If Consistency Measure (CM)>Th3 & Energy>Th4 then
Classify blocks to "good", average, poor, very poor

Threshold values are determined for valid local and global features taken into account. It maps quality of image blocks and overall structure to "good", "average", "bad" or"very noisy "identity.

2.3 Segmentation

Features for segmentation are selected according to assessment factor calculated. The range of features used for segmentation varies from simple variance, gradient variance, Energy concentration along dominant orientations, Dominant Ridge Score.

2.3.1 Energy Strength along Ridge Valley Orientations

The grey level gradient **(dx,** *dy)* at a pixel exhibits the orientation and the orientation strength of the image at this pixel. By performing Principal Component Analysis on the image gradients in an image block, an orthogonal basis for an image block can be formed by finding its eigen values and eigenvectors. The ratio between the two eigen values gives an indication of how strong the energy is concentrated along the dominant direction with two vectors pointing to the normal and tangential direction of the average ridge flow respectively. The covariance matrix C of the gradient vector for a N units image block is given by

$$C = \frac{1}{N}\sum\left\{\begin{bmatrix} dx \\ dy \end{bmatrix}\begin{bmatrix} dx & dy \end{bmatrix}\right\} = \begin{bmatrix} dx^2 & dxdy \\ dy & dy^2 \end{bmatrix} \quad \begin{bmatrix} c1 & c3 \\ c3 & c2 \end{bmatrix} \tag{4}$$

Where, dx and dy exhibit the intensity gradient of each pixel calculated by Sobel operator of 3 by 3 windows.

$$\text{MIN} = \frac{(c1+c2) - \sqrt{(c_1-c_2)^2+4c_3^2}}{2} \tag{5}$$

$$\lambda\ \text{MAX} = \frac{(c1 + c2) + \sqrt{(c_1-c_2)^2+4c_3^2}}{2} \quad (6), \qquad \text{OCL} = \frac{\lambda\ \text{MIN}}{\lambda\ \text{MAX}} \quad (7)$$

OCL values distribute between the range of [0, 1].OCL=0 means that ridges and valleys in a block change consistently in the same direction. While OCL=1 means that they are not consistent at all. These blocks may belong to the background with no ridges and valleys. For a small OCL value, ridges and valleys are very clear with good orientation consistency and, as the OCL value increases, they change irregularly. In the OCL images, the gray level of blocks indicates fingerprint images orientation consistency level.OCL value for image is obtained by summation of all the block values.

2.3.2 Local Gradient and Consistency Measure Based Method

In order to segment the foreground blocks effectively, the threshold values are defined for global and local gradient values along X values and Y values. The underlying idea for block segmentation is same as used in Junetal.[23] Foreground threshold is set by the following steps

1) Divide the input image I into non-overlapping blocks, size of blk* blk

2) Compute the gradients $\partial x(i,j)$, and $\partial y(i,j)$,at each pixel (i,j) which is the center of the block.

3) Calculate each block mean and variance value for x and y component of the gradient using the following equations:

$$Mx = \frac{1}{blk^2}\sum_{i=-\frac{blk}{2}}^{\frac{blk}{2}}\sum_{j=-\frac{blk}{2}}^{\frac{blk}{2}} \partial x(i,j) \ \ \& \ My = \frac{1}{blk^2}\sum_{i=-\frac{blk}{2}}^{\frac{blk}{2}}\sum_{j=-\frac{blk}{2}}^{\frac{blk}{2}} \partial y(i,j)\,.$$

where blk is the size of block.In our experiment block size is set to 8.

4) Compute deviation for both M_x and M_y using the equations:

$$Vx = \frac{1}{blk^2}\sum_{i=-\frac{blk}{2}}^{\frac{blk}{2}}\sum_{j=-\frac{blk}{2}}^{\frac{blk}{2}}(\partial x(i,j) - Mx)^2 \ \&$$

$$Vy = \frac{1}{blk^2}\sum_{i=-\frac{blk}{2}}^{\frac{blk}{2}}\sum_{j=-\frac{blk}{2}}^{\frac{blk}{2}}(\partial y(i,j) - My)^2 \tag{8}$$

5) Compute the Gradient Variance's mean:

$$VMx = \frac{1}{r*c}\sum_{i=1}^{r}\sum_{j=1}^{c} Vx \ \ , \ VMy = \frac{1}{r*c}\sum_{i=1}^{r}\sum_{j=1}^{c} Vy \tag{9}$$

6) Calculate the foreground regional variance estimate for x and y component of the gradient as follows:

$$Vfx = \frac{Vsx}{Nsx}, Vfy = \frac{Vsy}{Nsy}\ , \tag{10}$$

where VSx, Vsy and NSx, Nsy are defined respectively as blocks gradient sum and blocks gradient number along X axis and Y axis satisfying the condition, $Vx>=VM_x$ and $Vy>=VMy$

7) Calculating background regional variance estimate for x and y component of gradients:

$$Vbx = \frac{Vsfx}{Nbx} \; Vby = \frac{Vsfy}{Nby} \;, \tag{11}$$

Where VSfx, Vsfy and Nbx, Nby are defined respectively as blocks gradient sum and blocks gradient number along X axis and Y axis satisfying the condition Vx <=vfx and Vy<=Vfy

8) If Vx<Vbx and Vy<Vby, the block is considered as background otherwise it belongs to foreground.

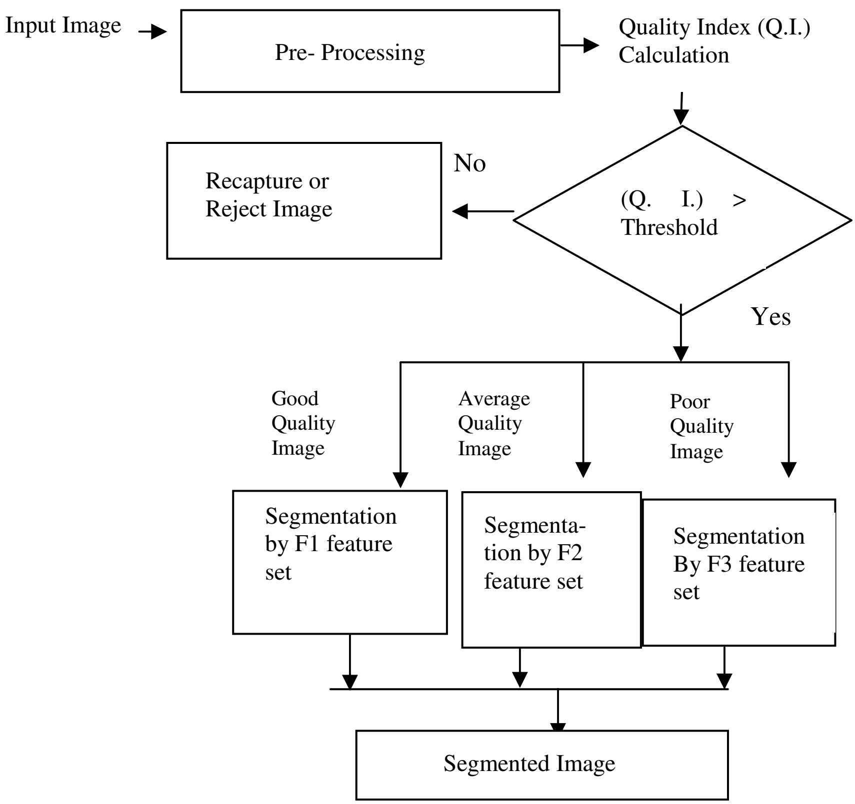


Fig. 1. FlowChart of Proposed Approach

Feature sets used in Approach F1: OCL and dominant Score; F2: Local Gradient and Consistency Measure; F3: Gray Variance Degree and consistency Measure

2.3.3 Dominant Ridge Score

The dominant ridge score, orientation of each pixel is obtained as:

$$\theta ij = 90° + \frac{1}{2} arctan\left\{\frac{2Gxy}{Gxx - Gyy}\right\} \tag{12}$$

where the gradients $Gx(i,j)$ is the sum of gradients along X axis in the block ,and $Gy(i,j)$,is the sum of gradients calculated along Y direction in the block. Gxy is the sum of the values of $Gx(i,j) * Gy(i,j)$ for a block .Gxx is the sum of square of the Gx values of the block .Gyy is the sum of the square of the Gy values of the block. Then orientation of each pixel is normalized to 8 normalized orientations (0, 22.5, 45, 67.5, 90, 112.5, 125 or 157.5). Then dominant ridge score is defined as:

$$n_{dom}/ n_w \tag{13}$$

where n_{dom} and n_w are corresponding, the number of block orientation and the number of pixels in block.

3 Experimental Results and Discussions

In order to validate the actual performance of the proposed approach described in the previous section, fingerprint images from FVC2004 DB3 databases are selected, which fingerprint images quality is poor. We evaluated the proposed method in three ways: 1) the estimation ability of quality, 2) segmentation between genuine foreground blocks and background area, 3) verification performance. The foremost parameter required for fingerprint recognition is segmentation area and in case of sample images the value is much higher than the required threshold.

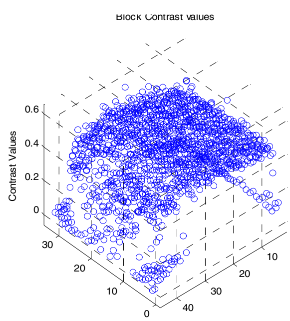


Fig. 2. Contrast measure of Good Quality Image

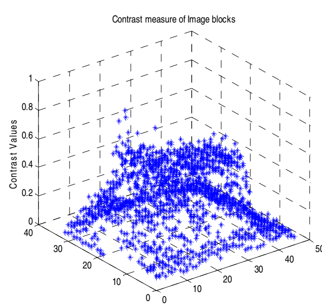


Fig. 3. Contrast measure of Poor Quality Image

In Fig.(2 & 3) those markers which have low contrast values are considered to be background .In Fig.2 large number of markers indicating blocks of image have contrast value greater than threshold value thereby predicting good quality of image. Fig.(4 &5) shows contrast measurement of the blocks of image. The markers which indicate higher consistency value represents the singular points present in the image..In fig.4 maximum number of blocks has good consistency measure except for the regions which are isolated or the regions which don’t contain any ridge area. The blocks which have poor orientation strength are considered to be background blocks.

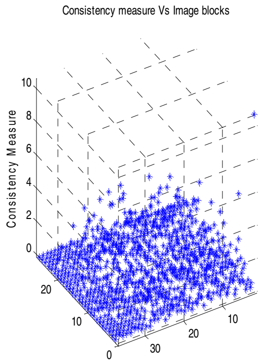


Fig. 4. Consistency Measure of Good Quality Image

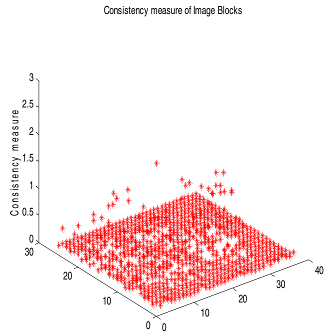


Fig. 5. Consistency Measure of Poor Quality Image

Table 1. Overall Quality Estimation of sample images from various attributes

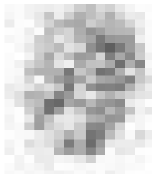
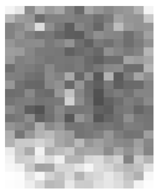
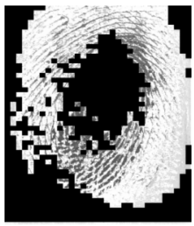
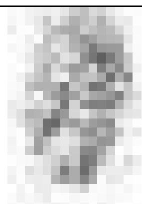
Image Id	**Total Number of Blocks in Image**	**Feature Set Under Evaluation**				**Quality Estima-tion**
		Effective Fore-ground	**Orienta-tion Strength**	**Consistency Measure**	**Energy Ratio**	
1	**1456.**	**83.17%**	**0.8856**	**89.91**	**79.98**	**Good**
2	**1456**	**74.13%**	**0.529**	**49.62**	**52.79**	**Poor**

Images in the first column are the original fingerprints. Second Column represents Quality map of the sample image. Third column fingerprints are segmented fingerprints using the traditional gradients, coherence, gray variance method. In fourth column segmented images with proposed approach are there. It can be seen that some fingerprints regions with low contrast or high noise still remain in the segmented fingerprints if we use traditional approaches of segmentation, which may generate spurious features during feature extraction.

Segmentation performance = T2/T1, where T2= Time to compute Minutiae points in original Image & T1= Time taken to compute minutiae points in Segmented Image

Segmentation performance for image (1)= T2/T1= 0.0356.
Segmentation performance for image 2 = T2/T1= 0.689(Poor).

Table 2. Overall Fingerprint Image Quality and Segmentation Analysis

Original Image	Quality Map	Segmentation using Coherence, Mean & Variance	Segmentation using Proposed Quality Based method
(1) 			
(2) 			
			

4 Conclusions and Future Work

In this paper, a new method for improving the robustness of the segmentation was proposed by defining image quality map. An attempt is made to correlate the image quality and segmentation performance. It is shown with the help of experiments that image features like gradients which produce very good results in case of good image may not produce good results in case of poor images which are inherently noisy and contain gray level fluctuations that generate wrong results.Future work will be concentrated to improve the combination of image features and hence image quality classification system by using genetic algorithm .Isolated low quality regions can be improved by reconstruction by Line adjacency information around blurred or broken areas.

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