Fingerprint Pore Extraction Based On Marker Controlled Watershed Segmentation

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***Abstract*— Automated Fingerprint Identification Systems (AFIS) have become a popular tool in many security and law enforcement applications. Most of these systems rely on the matching of fingerprints using the position and orientation of ridge endings and bifurcations within the fingerprint image. Sweat pores have been recently employed for automated fingerprint recognition, in which the pores are usually extracted by using a computationally expensive skeletonization method or through defining pore as isotropic or anisotropic models. In this paper, Extraction of pores is done by employing the Marker controlled Watershed Segmentation. Experimental results demonstrate that the method is effective even for 500 dpi images despite the common belief that images obtained at this resolution are not suitable for pore extraction. An explanation of the method is presented, the results are discussed, and future research possibilities are put forth.**

Keywords- sweat pores, skeletonization, pore model, marker controlled watershed segmentation.

I. INTRODUCTION

Automatic fingerprint recognition technologies currently have wide application for biometric person identification [1]. The purpose of an identification system is to check matching between the person's fingerprint with all fingerprint records, earlier enrolled and stored in the database. Use of such systems depends on discrepant requirements, first of all, identification reliability, matching speed and system cost. Though many identification algorithms [1][2] as well as commercial systems are proposed, achieving satisfactory fulfillment of all contradictory requirements is still an important problem. Most existing automated fingerprint recognition systems (AFRS) utilize only level 1 and level 2 fingerprint features (e.g. orientation field and minutiae) for personal identification [3][4]. Level 3 fingerprint features like pores, though seldom used by existing AFRS, are also very distinctive [5]. Only few researchers [5][6][7][8][9] are now exploring how to extract and use level 3 features in AFRS.

A common challenge to the pore-based fingerprint recognition systems is how to accurately and robustly extract pores from fingerprint images. Based on the position on the ridges, pores are often divided into two categories: open and closed. A closed pore is entirely enclosed by a ridge, while an open pore intersects with the valley lying between two ridges as shown in Fig.1.

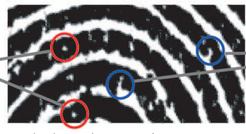

Fig. 1. Open and closed pores in a 1,000 ppi live-scan fingerprint image

II. BACKGROUND STUDY

To the best of the authors' knowledge, the first pore extraction method, proposed by Stosz and Alyea [6], binarizes and skeletonizes the fingerprint image. A pore is detected once some criteria are met while tracking the skeleton. This skeletonization-based method was later used in [5][7]. As pointed out in [9][10], however, skeletonization is computationally expensive and very sensitive to noise. It can work well only on very high resolution fingerprint images, e.g. the fingerprint images used in [5][6][7] were at least 2000dpi.

Recently, Ray et al. [10] proposed an approach to extracting pores from 500 dpi fingerprint images using a pore model which is a slightly modified 2-dimensional Gaussian function. Pores are found by locating local areas that can match to the pore model with minimum squared errors. This method uses a filter of universal scale to detect pores. However, it is hard, even impossible, to find a universal scale suitable to all pores. This is not true for open pores.

Very recently, Jain et al. [2][3] proposed to use Mexican hat wavelet transform to extract pores based on their observation that pore regions typically have high negative frequency response as intensity values change abruptly from bright to dark at the pores. The scale factor in this pore model is experimentally set with a specific dataset. This model is also limited by that the pore extractor cannot adapt itself to different fingerprints or different regions on a fingerprint.

Qijun Zhao,et al.[11] proposed an adaptive pore model (APM) based on the observation on real pore appearances. With the APM, a pore extraction method was then developed, whose parameters are adjusted adaptively according to the fingerprint ridge direction and period. The fingerprint image is partitioned into blocks and a local pore model is determined for each block. With the local pore

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model, a matched filter is used to extract the pores within each block.

Such models are not working effectively for images highly disturbed with background noise especially for rolled fingerprint images. Defining such models also increases complexity. In this paper, since pores appear on fingerprint images as blobs on the ridge , Marker Controlled Watershed Segmentation is introduced for pore extraction, a robust and flexible method for segmentation of objects with closed contours, where the boundaries are expressed as ridges .

III. WATERSHED TRANSFORM

The watersheds concept is one of the classic tools in the field of topography. It is the line that determines where a drop of water will fall into particular region. In mathematical morphology, gray-scale images are considered as topographic relieves. In the topographic representation of a given image *I*, the intensity value of each pixel stands for the elevation at this point. Assume that the image *f* is an element of the space *C(D)* of a connected domain *D* then the topographical distance between points *p* and *q* in *D* is,

$$T_f(p,q) = \inf_\gamma \int \| \Delta f(\gamma(s)) \| \, ds \qquad (1)$$

where $\inf_\gamma$ is over all paths (smooth curve) inside *D*, based on this Roerdink et al. [12] defines the watershed as follows.

Let $f \in C(D)$ have a minima $\{m_k\}_{k \in I}$,for some index set I. *CB* (m_i) *of a* minimum m_i is defined as the set of points. $C \in D$, which are topographically closer to m_i than to any other regional minimum m_j

$$\text{CB}(m_i) = \{x \in D \mid \forall_j \in I \setminus \{i\} : f(m_i) + T_f(x, m_i) < f(m_j) + T_f(x, m_j)\} \qquad (2)$$

The watershed of *f* is the set of points which do not belong to any catchment basin

$$W_{shed}(f) = D \cap \left(\bigcup_{i \in I} CB(m_i) \right) \qquad (3)$$

Let *W* be some label, $W \in I$. The watershed transform of *f* is a mapping of $\lambda : D \rightarrow I \cup \{W\}$ such that $\lambda(p) = i$ if $p \in CB(m_i)$ and $\lambda(p) = W$ if $p \in W_{shed}(f)$ .So the watershed transform of *f* assigns labels to the points *D* , such that (i) different catchment basins are uniquely labelled, and (ii) a special label *W* is assigned to all points of the watershed of *f* .

The advantage of the watershed transform is that, it produces closed and adjacent contours including all image edges. However, often the watershed produces a severe oversegmentation also. Some solutions of the over-segmentation are addressed in [13].

IV. MARKER CONTROLLED WATERSHED SEGMENTATION

The marker-controlled watershed segmentation has been shown to be a robust and flexible method for segmentation of objects with closed contours, where the boundaries are expressed as ridges [14]. Markers are placed inside an object of interest; internal markers associate with objects of interest, and external markers associate with the background. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbors.

A. Creating Markers

The marker image used for watershed segmentation is a binary image consisting of either single marker points or larger marker regions, where each connected marker is placed inside an object of interest. Each initial marker has a one-to-one relationship to a specific watershed region, thus the number of markers will be equal to the final number of watershed regions. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbors. The markers can be manually or automatically selected, but high throughput experiments often employ automatically generated markers to save human time and resources.

Various methods have been used for computing internal and external markers, many of which involve the linear filtering, non linear filtering and morphological processing. The method we choose for a particular application is highly dependent on the specific nature of images associated with that application

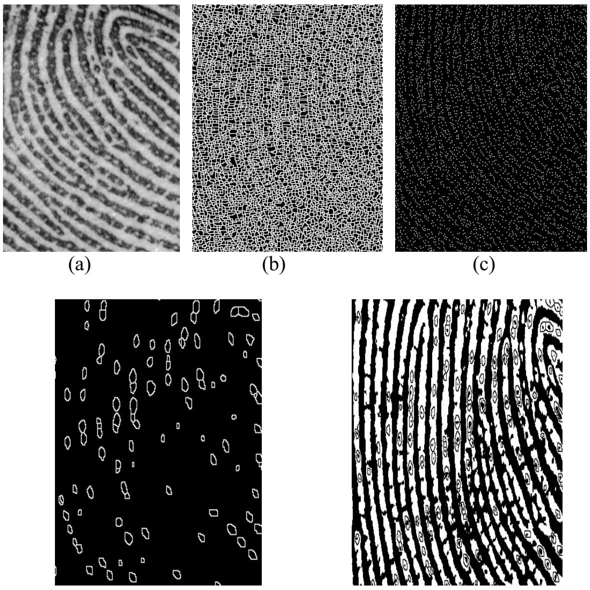
B. Pore Extraction

In this paper we used simple algorithm to create foreground and background markers using Morphological image reconstructions. The watershed transform of the gradient fingerprint image is computed without any other processing. The result is severely oversegmented due in part to the large number of regional minima as shown Fig.2 (b)

By computing the location of all regional minima in the fingerprint image as shown in Fig.2(c), we found that most of the regional minima are very shallow and represent detail that is irrelevant to our segmentation problem. The extraneous minima is eliminated by computing the set of low spots in the image that are deeper (by a height threshold = 2) than their immediate surroundings. Then the markers are superimposed on the original fingerprint image.

Next, background markers are created. The approach followed here is to mark the background by finding pixels that are exactly midway between the internal markers. This is done by computing the watershed transform of the internal marker image. The resulting watershed ridgelines appear in midway between the pores and hence they serve well as external markers. The marker image is shown in Fig.2(d)

The internal and external markers are then used to modify the gradient fingerprint image using a procedure called minima imposition. The minima imposition technique modifies a fingerprint image so that regional minima occur only in marked locations. Other pixel values are pushed up as necessary to remove all other regional minima. The gradient fingerprint image is then modified by imposing regional minima at the locations of both the internal and the external markers. Finally watershed transform of the marker-modified gradient fingerprint image is computed. After superimposing the watershed ridgelines on the original fingerprint image, a much improved pore extraction is obtained as shown in Fig.2(e)



(a) (b) (c)

(d) (e)

Fig.2 Pore extraction results for 1000dpi image
(a)Original image (b) Oversegmented image (c) Regional minima
(d) Marker image (e) Extracted pores

C. *Algorithm*

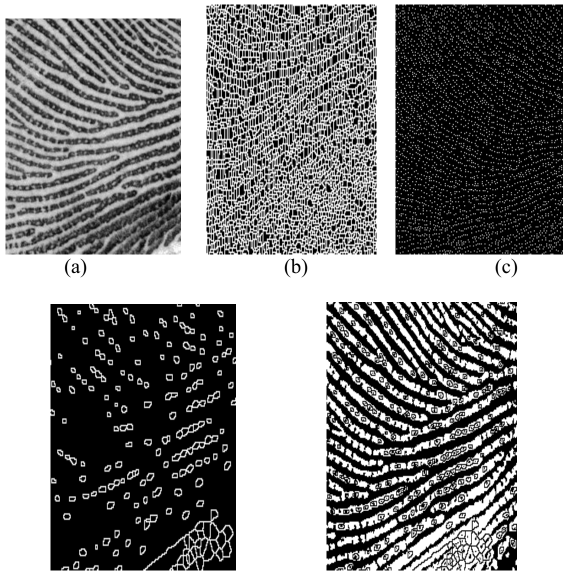
1. Read the gray-scale image.
2 .Develop gradient fingerprint images using appropriate edge detection function.
3. Compute the watershed transform of the gradient fingerprint image without any other processing.
4. Calculating the regional minima to obtain the good forward markers.

5. Superimpose the foreground marker image on binarised fingerprint image.
6. Clean the edges of the markers using edge reconstruction.
7. Compute the background markers.
8. Compute the watershed transform of the function.

V. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we present experimental result to demonstrate the performance of the proposed technique. The data set used in the experiments is the NIST SD27 dual resolution database, which contain rolled fingerprint images. The proposed method was also tested in 500 dpi fingerprint images and the Experimental results are shown in Fig.3

The results of employing the pore extraction method are very promising. The method also performs well on both 1000 dpi and 500 dpi images. The true detection rate *RT* (i.e. the ratio of the number of detected true pores to the number of all true pores) and the false detection rate *RF* (i.e. the ratio of the number of falsely detected pores to the number of all detected pores) were calculated on the fingerprint images. The average rates are listed in Table 1. The results show that the proposed method can extract pores more accurately and more robustly.



(a) (b) (c)

(d) (e)

Fig.2 Pore extraction results for 500dpi image
(a)Original image (b) Oversegmented image (c) Regional minima
(d) Marker image (e) Extracted pores

Table.1 Comparison of detection rate of the four methods

Performance measurement	**Proposed method**	**Qijun Zhao's**	**Jain's**	**Ray's**
True Detection Rate(R_T)	85%	82.8%	74.1 %	63.4 %
False Detection Rate (R_F)	12%	13.9%	22.2 %	20.4 %

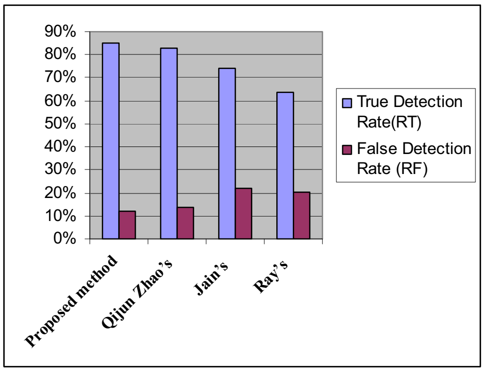


Fig.4 Comparison of the proposed method with the other methods

VI CONCLUSION

In this paper, a novel method for the extraction of pores from fingerprint images has been proposed. The steps involved in the extraction process have been outlined and some example results have been shown. The results show that this method holds promise for the use of pores by fingerprint identification systems. The presented pore extraction method has been compared with some existing schemes. The experimental results demonstrate that the proposed pore extraction method can detect pores more accurately and robustly, and can help to improve the verification accuracy of pore based fingerprint recognition systems.

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