Improving the Ridge Based Fingerprint Recognition Method Using Sweat Pores

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Abstract—**Among several biometric traits possible to be used for people identification, fingerprint is still the most used. Current automated fingerprint identification systems are based on ridge patterns and minutiae, classified as first and second level features, respectively. However, the development of new fingerprint sensors and the growing demand for more secure systems are leading to the use of additional discriminative fingerprint characteristics known as third level features, such as the sweat pores. Recent researches on fingerprint recognition have focused on fingerprint fragments, in which methods based only on first and second level features tend to obtain low recognition rates. This paper proposes a robust method developed for fingerprint recognition from fingerprint fragments based on ridges and sweat pores. We have extended a ridge-based fingerprint recognition method previously proposed in the literature, based on Hough Transform, by incorporating sweat pores information in the matching step. Experimental results showed that although the reduction of Equal Error Rate is modest, a significant improvement was observed when analyzing the FMR100 and FMR1000 metrics, which are more suitable for high security applications. For these two metrics, the proposed approach obtained a reduction superior to 10% of the rates, when compared to the original ridge-based approach.**

Keywords-biometrics; fingerprints; ridges; sweat pores

I. INTRODUCTION

In the modern society, several situations from secure login in information systems to prevention of terrorist attacks, make the personal identification in high safety mode a necessity. Traditionally, the common ways of personal identification are through possession, such as cards, keys, or documents, and knowledge, such as password or personal data.

However, these approaches present drawbacks, since a possession can be lost, stolen or used fraudulently by third parties, and knowledge can be forgotten or inferred by others. These vulnerabilities have been exploited by fraudsters, causing major leaks in the vaults of banks, consumers and service providers. As an alternative to these identification methods emerges Biometrics. Biometrics is the science of recognizing the identity of a person based on its physical or behavioral attributes such as face, fingerprints, voice, and iris [1].

Among many biometric traits, fingerprint is the most widely deployed biometric characteristic, because of its well-known distinctiveness (individuality) and persistence properties, as well as the low cost and maturity of products.

A fingerprint is the exterior appearance of the fingertip epidermis, produced when a finger is pressed against a plain surface [2]. The most evident structural characteristic of a fingerprint is the pattern of interleaved ridges and valleys [3], which appears in a fingerprint image as dark lines (ridges) or bright lines (valleys).

Fingerprint features are generally categorized into three levels [4][5]. First level features are the macro details of the fingerprint, such as the ridge flow, singular points, and pattern type. Second level features are the minutiae, such as ridge endings and bifurcations. Finally, third level features include some finnest attributes of the ridges, such as ridge path deviation, width, shape, pores, edge contour, incipient ridges, breaks, scars, and other permanent details [4]. Some examples of these three fingerprint level features are showed in Figure 1.
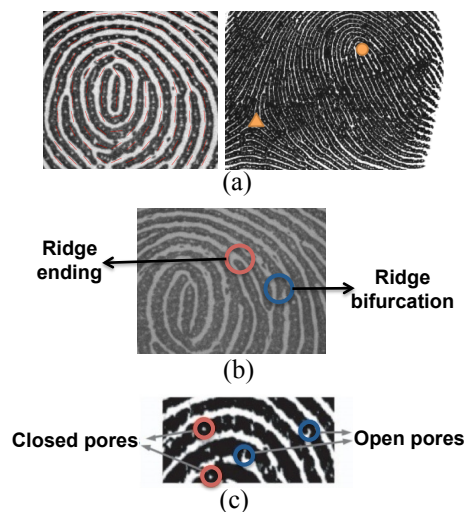

Figure 1. Some examples of fingerprint level features. (a) First level features (ridge orientation field and singular points), (b) Second level features (minutiae), and (c) Third level features (pores).

Statistical analysis show that first level features do not contain enough information to identify a person, however, they can be used for fingerprint classification and to reduce the search space. Second level features have sufficient discriminatory power to establish the individuality of fingerprints [6], and are considered permanents, immutables, and uniques by forensic experts. Likewise the second level, third

level fingerprint features are uniques for each individual, that is, they can provide discriminatory information for human identification [3].

In general, the current Automatic Fingerprint Identification Systems (AFIS) are based only on first and second fingerprint features [7], and require 500 dpi fingerprint images in order to extract the fingerprint characteristics. However, the Scientific Working Group on Friction Ridge Analysis, Study and Technology (SWGFAST) recommended, in 2005, the use of higher resolution images in order to allow the inclusion of third level features and follow the FBI standards [4].

Due to the new standards, the advent of high resolution fingerprint sensors, and the increasing requirements on the accuracy and robustness of the fingerprint recognition, researches have been developed to investigate and quantify the discriminatory power of third level fingerprint features [5][7][8][9].

Third level features are oftenly investigated by forensic experts when the other two levels are not enough to decide an identity, mainly when they are analysing fingerprint fragments. In such cases, the overlapping area of the two fingerprints being compared can be very small and, therefore, the reduced number of paired minutiae may be insufficient to permit a reliable fingerprint recognition [3].

With the trend of the reduction size of sensors in several applications, especially for mobile devices, the proper treatment of fingerprint fragments has great relevance.

The aim of this work is to propose and assess a third level features based fingerprint matching method, which extends the ridge-based fingerprint recognition method proposed by [10]. This new method incorporates sweat pores information in the fingerprint recognition stage, in order to improve the robustness and the reliability of the identification.

The rest of this paper is organized as follows. In Section II, we present a review of pore extraction methods. In Section III, the ridge-based fingerprint matching using Hough Transform, proposed by Marana and Jain [10], is described. In Section IV, we present the proposed approach for fingerprint recognition based on sweat pores, the evaluation database, and the assessment protocol. In Section V, we present the obtained results. Finally, in Section VI, we present the conclusions of this work and point future research directions.

II. REVIEW OF PORE EXTRACTION METHODS

The earliest pore extraction methods were based on skeletonization. Stosz and Alyea [11] used a custom-build sensor, whose resolution were around 2000 dpi. In their method, a preprocessing step is firstly applied, where the image is smoothed, binarized, and thinned to produce the raw skeleton image. From the skeleton, the terminations and the bifurcations can be easily found by examining the neighborhood of a pixel component of the skeleton. Termination

points have only one neighbor and bifurcation points have three neighbors, assuming that the skeleton pixels are eight-connected [11]. The pore detection is performed by tracking the skeleton. Each termination point is used as a starting location to track the skeleton. The tracking stage requires analyzing the current element, storing its coordinates, and determining the location of the next element in the path. The tracking algorithm proceeds until one of the stop criteria is satisfied: i) another termination point is detected, ii) a branching point is detected, and iii) the path length exceeds the maximum allowed value.

Afterwards, Kryszczuk et al. [12] worked with fingerprint fragments, in order to assess the performance of fingerprint recognition applied on images captured by small sensors, which are a tendency. They proposed an authentication system that can handle fingerprint image with reduced dimensions, but with high resolution. In order to align the ridges structures from the template and test images, first the ridge structures are cleaned using Gabor wavelet filtering, and then they calculate the 2D normalized correlation coefficient for every possible location of the fragment within the reference image. The decision on which part of the template image matches the test fragment is done by finding the highest correlation factor [12]. In order to detect the pores, they binarize the original grayscale image and look for closed pores, which are entirely surrounded by the ridge pixels and appear as holes in the ridges. Some heuristics are applied to remove spurious pores. So, to detect open pores (pores that intersects with a valley between two ridges), they skeletonize the valleys of the binarized image and compute the distance between the end of each spur and the skeleton of valleys. From the experiments the authors observed that the smaller are the fingerprint fragments, the better are the benefits of using sweat pores for fingerprint recognition.

However, as pointed by Jain et al. [4] the first methods proposed for fingerprint recognition based on pores have some drawbacks: i) skeletonization leads to some limitations due to its strong dependence on the image quality: ii) the alignment is computationally expensive; iii) they were validated by using small databases; and iv) only custom built optical sensors (2000 dpi), rather than commercially available live-scan sensors (1000 dpi) were used in these studies.

The next generation of pores detection methods were based on isotropic filters. Ray et al. [13] proposed a method to be applied on grayscale fingerprint images of 500 dpi, using an approach based on a modified 2D Gaussian function. First, this method calculates an error map for the image. Then, the map is binarized so that only areas of high pore probability are retained. Pores are detected in these areas as a local minimum in a neighborhood.

Posteriorly, Jain et al. [4][8] proposed a new pore detection method based on the observation that pore positions often give high negative frequency response as the intensity

values change abruptly from white to black. They used Gabor filters to enhance the ridges, this way separating ridges from valleys (since pores are naturally distributed along the ridges). And, to capture this abrupt changes, they apply the Mexican hat wavelet transform with an experimentally defined scale parameter. By adding the responses of both filters, they obtained an enhancement of pores, as well as of the borders between ridges and valleys, since pores are naturally distributed only along the ridges. Lastly, an empirically determined threshold (= 58) is applied to extract pores with blob size less than 40 pixels.

More recently, Zhao et al. [5] have investigated the spatial appearances of pores on fingerprint images, and have showed that some representative pore structures are not isotropic. In these cases, isotropic filter-based approaches do not work properly. Another limitation of isotropic approaches is that the pore extractor can not adapt itself, and the pore scales and ridge/valley widths can vary greatly from one fingerprint to another, or from one region to another in the same fingerprint [5]. Regarding this, Zhao et al. [5] proposed a Dynamic Anisotropic Pore Model (DAPM), which has two parameters to adjust: scale and orientation. These two parameters are adaptively determined according to the ridge frequency and orientation, respectively. The DAPM is defined as:

$$\begin{cases} P_0(i,j) = e^{(-j^2/2\sigma^2)} cos\left(\frac{\pi}{3\sigma}i\right) \\ -3\sigma \leq i,j \leq 3\sigma \end{cases} \quad (1)$$

$$\begin{cases} P_\theta(i,j) = Rot(P_0,\theta) = e^{(-j^2/2\sigma^2)} cos\left(\frac{\pi}{3\sigma}i\right) \\ \hat{i} = icos(\theta) - jsen(\theta), \hat{j} = isen(\theta) + jcos(\theta) \\ -3\sigma \leq i,j \leq 3\sigma \end{cases} \quad (2)$$

where Equation 1 is the zero-degree model and Equation 2 is the rotated model. In these equations σ is the scale parameter (to control the pore size) and θ is the orientation parameter (to control the direction of the pore model). To apply the DAPM, Zhao et al. [5] use a block-wise approach, where the blocks are classified into three kinds: well-defined (where the ridge orientation and frequency are directly estimated), ill-posed (where the parameters are estimated by interpolation the neighboring blocks), and background blocks. The block partition is performed in a hierarchical way, starting with a large block size and analyzing the consistency of ridge orientation and the intensity contrast, in order to classify the block. Background blocks are excluded, well-defined blocks are recorded and are not further partitioned. On the other side, a block larger than the minimum size is partitioned into four equal sub-blocks and are further examined [5]. After the fingerprint partition and parameters estimation, the ridge map is extracted. So, the pores are detected, using the DAPM based detection to well-defined blocks, and an Adaptive Difference of Gaussians (DoG) based, proposed in [9], to ill-posed blocks. The ridge map is then used to mask the pore detection response, since the pores lies on the

ridges. Finally, pos-processing steps are applied to remove false detections (pores with very low intensity, out of the specified size range).

In our approach, we choose the DAPM based pore extraction, since according to the literature review this method has the best average pore detection accuracy. Figure 2 shows two examples of pore extraction using DAPM method.
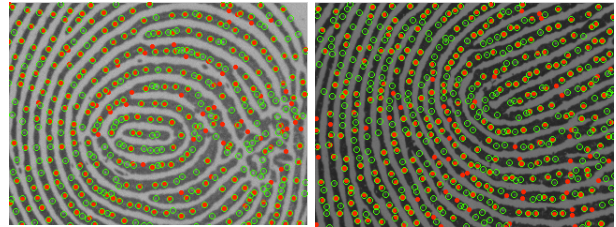

Figure 2. (Color online) Examples of pore extraction resulted using DAPM method. The ground truth pores are in green, and the DAPM detected pores are in red.

III. RIDGE-BASED FINGERPRINT MATCHING USING HOUGH TRANSFORM

In the ridge-based fingerprint recognition approach proposed by Marana and Jain [10], the features extraction stage is composed by three main steps: i) Ridge extraction and thinning: based on the method adopted in [14], where firstly the fingerprint orientation field is estimated, so the fingerprint area is separated from the background and after the ridges are extracted and thinned; ii) Straight line extraction: the most significant straight lines that lie on the fingerprint ridge pixels are extracted using the Hough transform; iii) Ridges classification: using the straight lines associated to a ridge, it is computed the ridge curvature, and then, based on such curvature, the ridge is classified into one of five categories ranging from category 1, in which the ridge seems a straight line, to category 5, in which the ridge seems a loop line. Figure 3, extracted from [10], illustrates the ridges extraction stage.
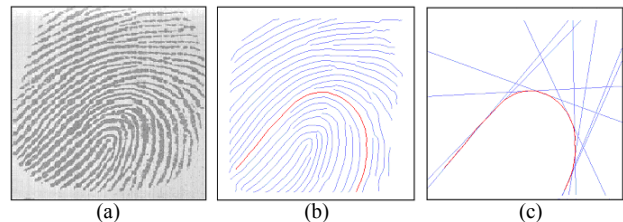

Figure 3. (Color online) Ridges extraction stage. (a) Fingerprint image; (b) Thinned ridges detected from the fingerprint; (c) Straight lines detected from a given (highlighted) fingerprint ridge by using the Hough Transform [10].

The fingerprint matching consists in two main steps: i) Registration: in which the translation and rotation parameters are estimated to align the query fingerprint image with the

template, using the Hough space peaks; ii) Comparison: in which the ridge matching score (RS) is calculated from the ridge alignment matrix C as follows:

$$RS = \frac{2\left(\sum_{i=1}^{n_1}\sum_{j=1}^{n_2} C(i,j)^2\right)}{a+b} \qquad (3)$$

where n_1 and n_2 mean the numbers of ridges of the query and template images, respectively, and a and b are defined by Equation 4 and 5.

$$a = \sum_{i=1}^{n_1}(R_q(i)_{nop})^2 \qquad (4)$$

$$b = \sum_{i=1}^{n_2}(R_t(i)_{nop})^2 \qquad (5)$$

where $R_q(i)_{nop}$ is the number of pixels of the *i-th* ridge of query fingerprint, and $R_t(i)_{nop}$ is the number of pixels of the *i-th* ridge of the template fingerprint. Only the ridges of one fingerprint image that intercepts at least one ridge of the other fingerprint image are considered in the computation of a and b.

Figure 4 shows the matrix of ridge alignments obtained from a genuine and an impostor fingerprint matching. In the genuine case, high-valued peaks are mostly spread along the matrix's main diagonal. On the other hand, in the impostor case, low-valued peaks are spread over the matrix [10].
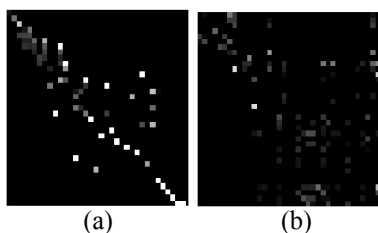

(a)   (b)

Figure 4.   Matrix of ridge alignments obtained from (a) genuine fingerprint matching, and (b) impostor fingerprint matching.

IV. PROPOSED METHOD

Analyzing the ridge-based method proposed by Marana and Jain [10], we can observe that one of its weaknesses is that some impostor matchings can generate high scores, especially when only fragments of fingerprints are compared.

The aim of this work is to extend this ridge based fingerprint recognition method using sweat pores information in the fingerprint matching step, focusing on fragments of fingerprints. The method used to extract pores is the DAPM, proposed by Zhao et al. [5]. Figure 5 presents a diagram illustrating the proposed approach.

Firstly, there is a preprocessing step, based on Hong et al. work [14], in order to enhance the fingerprint input images,
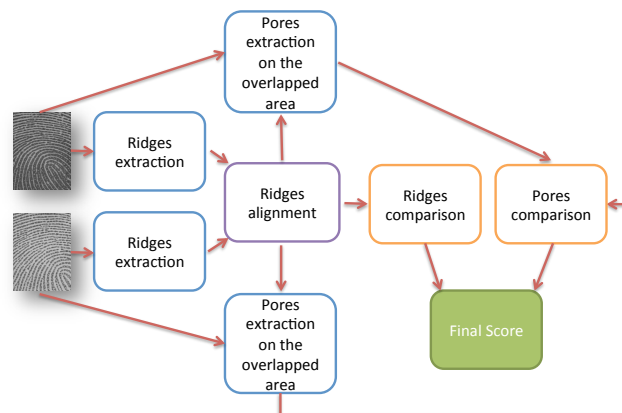

Figure 5.   Proposed approach using two kinds of third level features (ridges and pores).

and to extract the orientation field and the frequency from the ridges.

The preprocessing output and the parameters extracted from the ridges are used by both methods, the ridge-based and the pore-based. So, to the ridge-based fingerprint recognition method, we down-sample the enhanced images and then execute the extraction, alignment and matching steps.

The alignment obtained by the ridge-based method is used to register the query and the template images. Then, after the alignment, the sweat pores are extracted only in the overlapped area. We use the original image instead of its downsampled version, because pore detection requires high resolution images. The ridge orientation and frequency obtained in the preprocessing step are used to compose the parameters of the DAPM. After the pore extraction and the post-processing, we label the pores according to the ridge where they are located.

For the pore matchings, we have adopted a correlation-based method, and, due to the natural fingerprint distortion, we use a bounding box around the detected pores in the template image in order to establish the pairwise correspondence with the detected pores in the query image. To increase the confidence of the pore matchings, we use the matched ridges information calculated by means of Marana and Jain method [10], taking the peaks of the ridge alignment matrix C and analysing the pores labels.

The pore matching score is calculated following the Equation 6.

$$PS = \frac{|MP|}{min(T_{nop}, Q_{nop})} \qquad (6)$$

where MP is the matched pores set, $|MP|$ denotes the number of elements in the set MP, T_{nop} and Q_{nop} are the number of pores found in the fingerprints overlapped area from the template and query images, respectively.

Lastly, the scores calculated for the ridges and the pores matchings are combined through the weighted sum scheme.

To assess the proposed approach, we have used a public database containing partial fingerprints with high resolution. In the next subsections, we describe the database, the protocol, and the score fusion strategy adopted in this work.

A. Database

To assess the proposed approach we have used The Hong Kong Polytechnic University (PolyU) High-Resolution-Fingerprint (HRF) Database [15]. We have used the test set from the database PolyU HRF DBI, which consists of 1480 partial fingerprint images of 148 fingers. These fingerprints were collected in two sessions, separated by two weeks apart. In each session, five images of each finger were captured, using a custom built sensor, with resolution of 1200 dpi, generating fingerprint images of 320x240 pixels. When the database was captured, the participants were asked to naturally put their fingers on the prism of the scanner, without any exaggeration, in order to avoid severe fingerprint deformation.

The PolyU HRF database is very challenging. Besides presenting the most common problems, such as non-linear distortions, rotations, and translations, the overlapping area of the partial fingerprint is very small, making difficult to register properly the fingerprints. Figure 6 shows some samples of the PolyU HRF DBI test set.
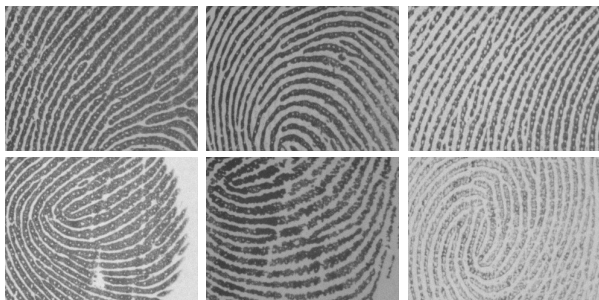

Figure 6. Some samples from the PolyU HRF DBI test set fingerprint images.

B. Protocol

In order to evaluate the performance of the proposed method for fingerprint recognition based on ridges and pores, we have performed experiments according to the following:

- *Genuine comparisons:* each fingerprint image of the second session was compared with the five fingerprint images of the first session of the same individual, totalizing 3,700 genuine comparisons;
- *Impostor comparisons:* the first fingerprint image of the second session of an individual was compared with the first fingerprint image from the first session of all other individuals, totalizing 21,756 impostor comparisons.

With all genuine and impostor matching scores we have calculated three metrics: EER (Equal Error Rate), the error rate at a given threshold where the False Match Rate (FMR) and False Non-Match Rate (FNMR) have the same value, FMR100 (value of FNMR for FMR = 1/100), and FMR1000 (value of FNMR for FMR = 1/1000) [16].

C. Score analysis

In the experiments, we have analyzed the recognition accuracy for three situations: i) using only ridge matching scores; ii) using only pore matching scores (but, using the ridges for alignment and labeling); and iii) using the fusion of ridge and pore matching scores, through the weighted sum scheme, calculated as follow:

$$FS = \omega.RS + (1 - \omega).PS, \qquad (7)$$

where RS is the ridge matching score, PS is the pore matching score, ω is the weight for RS ($\omega \in [0, 1]$).

V. EXPERIMENTAL RESULTS

Figure 7 presents the EER using only ridges ($\omega = 0$), pores ($\omega = 1$), and varying the associated weight for each score. In the best case, the EER decrease from 23,50% (original ridge-based algorithm) to 22,30% using pores information together.

Figure 8 shows the FMR100 and the FMR1000, varying the weight of pores with respect to ridges. As shown in this Figure, combining the scores, the proposed approach reaches significant improvements, with reductions above 10% compared to the original ridge-based method. The original ridge-based method obtained 87,03% of FMR1000 and 68,70% of FMR100. After the fusion with pores matching scores, the FMR1000 reduced to 76,21%, and the FMR100 reduced to 57,81%.
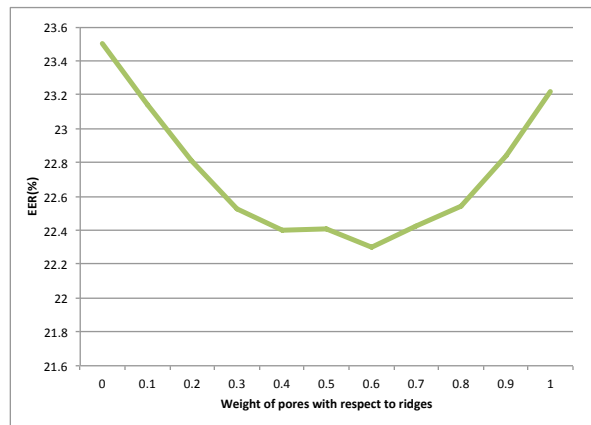

Figure 7. The EER of proposed approach when different weights to pore score are used.

The high error rates obtained in the experiments may be explained by the adopted database, which, as said, is very
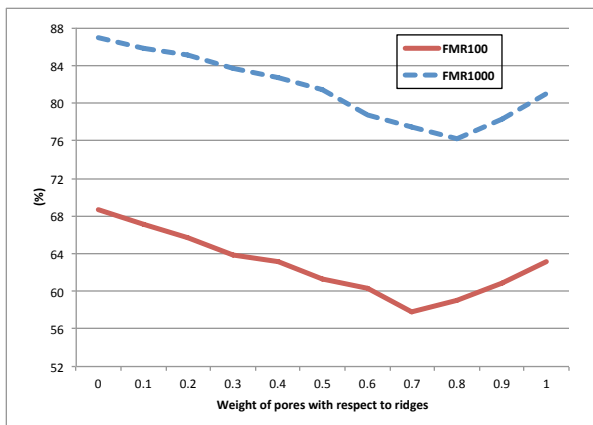
Figure 8. The FRM100 and the FMR1000 of proposed approach when different weights to pore score are used.

challenging, since it is composed of fingerprint fragments, which lead to small overlapping areas during the fingerprint matchings.

Table I reports the experimental results obtained on PolyU HRF Database following the protocol described in section IV-B. The best result was obtained when the ridge matching scores were fused with the pore matching scores.

Table I
COMPARATIVE RESULTS OBTAINED IN THE EXPERIMENTS.

Rate	Ridge-based	Pore-based	Ridge and Pore-based
EER	23,50%	23,22%	22,30%
FMR100	68,70%	63,19%	57,81%
FMR1000	87,03%	80,97%	76,21%

VI. CONCLUSIONS AND FUTURE WORK

This paper presents a fingerprint recognition technique that uses two kinds of third level fingerprint features: ridges and sweat pores. The ridge-based fingerprint matching method, proposed by Marana and Jain [10], used as start point, is extended to incorporate sweat pores information in the matching step. The alignment obtained by the ridge-based method is used to register the query and the template. Then, the pores obtained from the fingerprints, by using the DAPM pore extraction method, are used in the matching step to increase the confidence and performance of the matching.

The proposed approach obtained a reduction of more than 10% in FMR100 and FMR1000, comparing with the original ridge-based algorithm, when applied on a public database composed of fingerprint fragments. These results proved that the use of sweat pores can improve the fingerprint recognition rates in applications where the fingerprint sensor has high resolution and a reduced sensing area.

In order to continue the investigation with sweat pores, we intend to evaluate their use in other steps of the fingerprint recognition process, such as in the alignment. We also intend

to test and compare the current approach against commercial minutiae-based methods, and investigate the best approaches to combine ridges and pores based methods.

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