

Fingerprint Pore Characteristics for Liveness Detection

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Abstract: In the search for viable fingerprint liveness detection techniques, one looks for unique characteristics that distinguish the friction ridge skin of a living finger from all other materials that could be made to imitate it. One such characteristic is the perspiration phenomenon, where small openings in the skin called pores, positioned periodically along the ridges, excrete sweat. These pores are often visible in images captured by a fingerprint scanner. This paper proposes an approach to fingerprint liveness detection, where pores are detected and a small region around each pore is analyzed to determine the perspiration activity. Results are presented using the LivDet 2011 and 2013 datasets, showing that the proposed approach is viable as a fingerprint liveness detection approach on its own and improves performance when combined with other liveness detection approaches.

1 Introduction

Circumvention is an issue becoming of greater concern in the current state of biometric system development. A biometric system is vulnerable to many types of attacks that can undermine its integrity and reliability. This paper focuses specifically on attacks aimed at the sensor of a biometric system. Any such presentation, which is made with the intent to circumvent the normal operation of the system, is referred to as a presentation attack. A specific type of presentation attack is an artificial presentation attack, involving forgery of a biometric trait, commonly termed “spoofing”.

In biometric systems, the goal of liveness detection is to determine if the biometric being captured is an actual measurement from the authorized, live person who is present at the time of capture. Liveness detection reduces the risk of spoofing by requiring a liveness signature in addition to matched biometric information. No system is perfect in its ability to prevent spoofing attacks. However, liveness algorithms can reduce this vulnerability to minimize the risk of spoofing.

Pores, being level-3 fingerprint features have been utilized for fingerprint matching, as in the works of Jain et al. [JCD07] and Abhyankar and Schuckers [AS10]. Although these approaches may have inherent liveness detection capabilities, given that pores are often

not represented the same in fake fingers as in live, the goal is pattern matching of located pores. The approach described in this paper looks more in depth at the characteristics of the pores, giving detailed information on the source of the fingerprint, i.e. from a live or fake finger.

Pore detection has been briefly studied as a measure for fingerprint liveness detection [GMR12], [MRT10]. The features used in these previous studies characterize the number of pores detected in fingerprint images and Euclidian distances between pores [MRT10]. The assumption here is that pores are less likely to appear in spoofed fingerprint images than in live captured fingerprint images. As methods for creating fake fingers become more advanced, the quality of spoofed fingerprint images will continue to improve. Consequently, more accurately and consistently representing pores in a fake finger is becoming less of an issue for skilled imposters. The alternative then is to analyze detected pores in terms of their perspiration activity. Manivanan et al. [MMB10] introduced a method for detecting active sweat pores using highpass and correlation filtering on images collected using a micro-capture camera. In this paper we propose a simple, efficient approach to active sweat pore classification using only the supplied gray-scale fingerprint image.

The remainder of this paper is organized as follows. Section 2 presents the proposed approach for analyzing fingerprint pores for detection of perspiration activity. Section 3 presents the performance results obtained using the datasets of the LivDet 2011 and 2013 fingerprint liveness competitions. Finally, Section 4 ends with the conclusion.

2 Analysis of fingerprint pores

Given that pores are level-3 features, the ability to detect pores is dependent on the resolution of the fingerprint image. Generally, it has been determined that pores can only be reliably extracted from fingerprint images if the resolution is greater than or equal to 1000 dpi [JCD07], [Zh10], [Zh11]. However, some approaches have been proposed to do this task on fingerprint images with resolutions near 500 dpi [MRT10], [RMA05].

A pore visible on a ridge segment can be classified as either open or closed depending on whether it is emitting sweat or not [JCD07]. An open pore is one that is emitting sweat and will open out into the valley on one side. A closed pore on the other hand, will appear as a closed circle in the center of the ridge. Open and closed pores can be seen in an example fingerprint image presented in Fig. 1.

A number of features can be used to characterize sweat pores in a fingerprint image. One type of feature group is representative of the number of pores detected and the pore-to-pore spacing. Depending on the process used for creating a fake finger, this feature may be more or less useful for liveness detection. For example, in the LivDet 2013 competition, two of the datasets (Biometrika and Italdata) were created using the non-cooperative method (from latent prints) [Gh13]. For these particular images, level-3 features are mostly nonexistent and merely counting the number of detected pores and/or the spacing between pores can be a robust liveness detection method in itself. To

illustrate this, pairs of live/spoofed fingerprint images from the LivDet 2011 and LivDet 2013 Biometrika datasets are compared in Fig. 3 and Fig. 4 respectively. The lack of pores in the right image of Fig. 4 is apparent. For this feature group, the frequency at which pores appear along the ridge segments is extracted by measuring the number of pixels between each pair of pores while tracking the centerline of each ridge segment. In addition to the pore spacing features, the total number of pores detected relative to the total length of all ridge segments is determined.

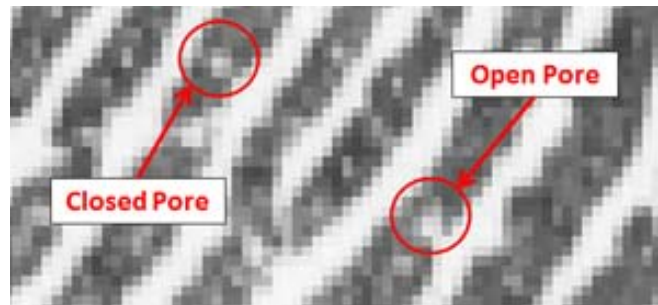


Fig. 2: Example fingerprint image with open and closed pores present.

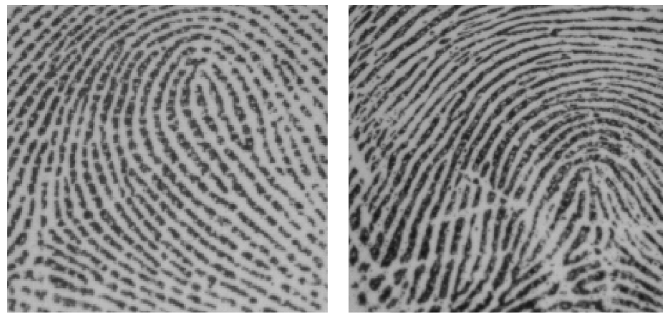


Fig. 3: Example live fingerprint image (left) and spoofed fingerprint image (right) from the LivDet2011 Biometrika dataset [Ya12].



Fig. 4: Example live fingerprint image (left) and spoofed fingerprint image (right) from the LivDet 2013 Biometrika dataset [Gh13].

One of the key attributes of a live finger, distinguishing it from a fake finger, is in the perspiration phenomenon. By analyzing the gray level distribution around individual pores, information regarding the perspiration activity of each pore can be assessed. As was stated above, a sweat pore can be either open or closed depending on whether it is emitting perspiration or not. Given that a fake finger should not be emitting perspiration, identification of open pores would provide evidence that the finger is alive, though with a great deal of effort it is possible that a forger could fashion open pores on a fake finger. Additionally, by analyzing the gray level distribution around each pore, the diffusion of perspiration coming out of a pore into the surrounding region can be measured. This can be accomplished by following a circular path at some radius around the pore center. The pixels in this path are analyzed by calculating gray level variance and maximum gray level difference. This feature adds robustness to the approach when presented with more realistic fake fingers, such as those obtained using the cooperative method (direct impression of the live finger in a mold for making the fake finger), such as the Cross Match dataset from LivDet 2013 [Gh13] and the four datasets from LivDet 2011 [Ya12].

2.1 Feature extraction

In this approach, pore centers are identified by searching the ridge segments for local maxima in gray level, satisfying certain threshold criteria. A pore appears as a small peak in the ridge (whiter pixels have a higher grayscale value), by doing a search using a circular derivative operator to identify local maxima in the ridge signal and setting appropriate thresholds, pores can be identified. Given a fingerprint image $I(x,y)$, and converting to polar coordinates to get $I(r \cos \theta, r \sin \theta)$, the operator with decision criteria at each point (x,y) within the boundaries of the ridge can be defined as in Equation 1.

$$\sum_{\theta=0}^{2\pi} -\frac{d}{dr} I(x + r \cos(\theta), y + r \sin(\theta)) > threshold \quad (1)$$

The feature extraction process is as follows: First the fingerprint image is converted to a binary image, distinguishing the ridges from the valleys. Next, the binary ridge segments are thinned to a single pixel wide skeleton, which identifies a centerline for each ridge segment. This skeleton is then followed and the pore searching algorithm described by Equation 1 is implemented. In Equation 1, the maximum value of radius r is defined based on the resolution (in dpi) of the fingerprint image. The threshold can be set to a constant value for all images or may be pre-computed for each image based on the statistics of the gray level distribution of the image. In this paper, a constant threshold is chosen. Once a pore is identified, the statistics of the gray level values in a circular path of radius d around the pore, such as gray level mean m_g , variance σ_g^2 , and maximum gray level difference D_g are analyzed. The corresponding calculations are shown in Equations 2 – 4. The distance from the previous pore center to the current one is then measured, giving the pore-to-pore spacing along ridge segments. For the following experiments, carried out on 500 dpi images, the radius of the circular path around each pore is set to 2 pixels.

$$m_g(x, y) = \frac{1}{2\pi} \sum_{\theta=0}^{2\pi} I(x + d \cos(\theta), y + d \sin(\theta)) \quad (2)$$

$$\sigma_g^2(x, y) = \frac{1}{2\pi} \sum_{\theta=0}^{2\pi} (I(x + d \cos(\theta), y + d \sin(\theta)) - m_g(x, y))^2 \quad (3)$$

$$D_g(x, y) = \max_{\theta} \left(I \left(\begin{matrix} x + d \cos(\theta) \\ y + d \sin(\theta) \end{matrix} \right) \right) - \min_{\theta} \left(I \left(\begin{matrix} x + d \cos(\theta) \\ y + d \sin(\theta) \end{matrix} \right) \right) \quad (4)$$

After the above described characteristics are extracted from the fingerprint, the distributions are represented by histograms. Pore spacing, pore region gray level variance, and pore region maximum gray level difference are each represented by a 10 bin histogram. Adding on an additional feature to represent the total number of pores detected gives a total of 31 features.

2.2 Classification

The extracted features are classified as live or fake using a support vector machine (SVM) classifier with a radial basis function (RBF) kernel. The LIBSVM software package [CL11] is used for this task. The error terms used in the performance evaluation for the LivDet competitions are FerrFake for the proportion of spoofed images misclassified as live and FerrLive for the proportion of live images misclassified as spoofed. The FerrFake and FerrLive error terms correspond to the attack presentation classification error rate (APCER) and normal presentation classification error rate (NPCER) respectively, as defined in the ISO/IEC 30107-3 WD standard. In this paper, the equal error rate (EER), i.e. the decision threshold at which the APCER equals the NPCER is used for performance comparison.

3 Results

The fingerprint images from the LivDet 2011 and LivDet 2013 liveness detection competitions are used for the following evaluation. The LivDet 2011 dataset consists of live and spoofed images from four different devices; Biometrika FX2000, Digital Persona 4000B, Italdata ET10, and Sagem MSO300. For each device, 2000 live and 2000 spoofed images were collected. The live and spoofed images from each device are then divided equally into training and testing subsets. The LivDet 2013 dataset is similarly constructed with images collected from a Biometrika FX2000, Italdata ET10, Cross Match L SCAN GUARDIAN, and an unidentified swipe sensor. The swipe sensor was excluded from this evaluation since the proposed algorithm is currently not designed to process the raw stretched out images provided. For this dataset, 2000 live and 2000 spoofed images were collected from the Biometrika and Italdata devices and 2500 live and 1000 spoofed images were collected from the Cross Match device. Once again these images were equally divided into training and test subsets. The following evaluation is

conducted by training the algorithm on the specified training data and evaluated using the corresponding testing data [Gh13], [Ya12].

The proposed pore analysis approach is first tested on the four LivDet 2011 datasets. Additionally, the proposed features are fused with previously developed liveness features to analyze the performance improvement when adding the proposed pore features to an already existing baseline liveness detection algorithm. This baseline liveness detection algorithm is composed of intensity features [TS06], ridge signal statistics [TS10], and valley noise [TS08].

The performance results for the LivDet 2011 datasets are presented in Table 1. For comparison, the results from the LivDet 2011 competition [Ya12] are also presented, along with more recent performance results using that dataset presented by Ghiani et al. [GMR12], which includes results from the pores detection approach of [MRT10]. Since the LivDet competition results are presented as FerrFake and FerrLive at a fixed threshold, the corresponding EER is estimated by calculating the half total error rate (HTER), which is the average of FerrFake and FerrLive. Comparing the results from our fingerprint pore analysis with that of [MRT10], we see an improvement of 7.5% when averaging the EERs across all of the datasets. Also, it is worth noting that when combining the pore features with the baseline algorithm, liveness detection performance is improved on average.

Table 1: LivDet 2011 performance results presented as EERs. For the LivDet 2011 results, EERs are estimated by averaging FerrFake and FerrLive.

		Biometrika	Italdata	Digital	Sagem	EER Mean
Proposed Approach	Pore Analysis	26.6%	31.4%	23.4%	22.0%	25.9%
	Baseline	20.6%	14.0%	8.4%	8.4%	12.9%
	Fusion	18.4	15.2%	7.8%	6.7%	12.0%
State of the Art [GMR12]	LBP	11.0%	19.0%	10.6%	8.4%	12.3%
	LBP+LBQ	10.4%	13.2%	8.0%	5.3%	9.2%
	Pore Detection	27.4%	28.8%	35.9%	41.6%	33.4%
LivDet 2011 Results [Ya12]	Dermalog	20.0%	21.8%	36.1%	15.3%	23.3%
	Federico	40.0%	40.0%	8.9%	13.5%	25.6%
	CASIA	33.9%	26.7%	25.4%	22.9%	27.2%

Next, the proposed pore analysis approach is tested on three of the LivDet 2013 datasets. This analysis shows the increased benefit of fingerprint pore analysis when level-3 detail is not represented on the fake fingerprints, such as in the Biometrika and Italdata sets. The results for the LivDet 2013 datasets are presented in Table 2. The performance of the proposed approach is compared to the top performer on each of the three datasets from the LivDet 2013 competition [Gh13]. The pore analysis works so well for these datasets, particularly for Biometrika and Italdata, that the optimal performance was obtained using only the pore analysis.

Table 2: LivDet 2013 performance results presented as EERs. For the LivDet 2013 results, EERs are estimated by averaging FerrFake and FerrLive.

		Biometrika	Italdata	Cross Match	EER Mean
Proposed Approach	Pore Analysis	2.2%	1.0%	34.9%	12.7%
	Baseline	2.4%	2.5%	38.4%	14.4%
	Fusion	2.0%	1.6%	39.6%	14.4%
LivDet 2013 Results [Gh13]	Dermalog	1.7%	0.8%	49.9%	17.5%
	Anonym2	1.8%	0.6%	49.4%	17.3%
	UniNap1	18.2%	3.5%	31.2%	17.6%

The contribution of fingerprint pore analysis to liveness detection is somewhat dependent on the particular data on which it is used. These data factors can be related to the sensing technology as well as the types of spoofing attacks that may be used against the particular system. For example, when fake fingers are created from latent prints such as those included in the LivDet 2013 Biometrika and Italdata datasets, simply counting the number of detected pores might be enough for a robust liveness detection method. However, when more realistic fake fingers are created, where level-3 features (e.g. pores) are accurately replicated on the fake finger, characteristics of the area surrounding each pore should be relied more heavily upon than the number of pores detected. Additionally, higher quality fingerprint scanners that can more accurately image the fine detail around a pore should be able to better utilize these features than a lower quality scanner.

4 Conclusion

A fingerprint pore analysis approach is presented, which combines the approach of analyzing the distribution of detected pores with an analysis of gray level distribution around each pore center. The added benefit of the latter analysis is that even when pores are represented accurately in high quality fake fingers, the pores can be classified in terms of their perspiration activity. The performance results obtained using the datasets of the LivDet 2011 and 2013 competitions show that the proposed approach is able to improve performance when added to an existing liveness detection method. The approach may even provide the best results when used as a stand-alone for the cases where an imposter is not able to retain the pores during the creation of a fake finger.

At this point in time, only optical fingerprint devices have been analyzed, for future work, additional sensing technologies will be evaluated for their compatibility with the proposed fingerprint liveness detection approach. As techniques for creating fake fingers for fingerprint spoofing are further advanced, with pores being represented more accurately, the proposed approach may become less viable. Therefore, further development of the methods for characterizing pores will be explored to increase robustness.

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