Fingerprint liveness detection using Binarized Statistical Image Features

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Abstract

Recent experiments, reported in the third edition of Fingerprint Liveness Detection competition (LivDet 2013), have clearly shown that fingerprint liveness detection is a very difficult and challenging task. Although the number of approaches is large, none of them can be claimed as able to detect liveness of fingerprint traits with an acceptable error rate. In our opinion, in order to investigate at which extent this error can be reduced, novel feature sets must be proposed, and, eventually, integrated with existing ones. In this paper, a novel fingerprint liveness descriptor named "BSIF" is described, which, similarly to Local Binary Pattern and Local Phase Quantization-based representations, encodes the local fingerprint texture on a feature vector. Experimental results on LivDet 2011 data sets appear to be encouraging and make this descriptor worth of further investigations.

1. Introduction

In the last decade it has been repeatedly proved that a fingerprint verification system can be deceived by fake fingerprints. As a matter of fact standard sensors are not able to distinguish images of a real fingertip from those of an artificial replica.

In Fingerprint Liveness Detection additional information is used to verify if a fingertip image is authentic. Hardware-based systems use additional sensors to gain measurements outside of the fingerprint image itself to detect liveness (biometric measurements as that of the heartbeat or the blood pressure on the fingertip) [4]. Software-based systems use image processing algorithms to gather information directly from the collected fingerprint to detect liveness [4]. This work is focused on software-based systems.

Over the years several algorithms based on the measurement of live-based characteristics (the shape of ridges, the pores presence or the perspiration), or the measurement of the amount of details lost and the presence of artifacts during the fake production [12, 3, 9] have been proposed. These algorithms extract from a fingertip image a certain number of features that will be used to classify the fingerprint as either live or fake. If initially most of them seem to provide satisfying results, the introduction of new spoofing materials, beside the LivDet event, led to a general error rate increase [16, 5]. Among others two texture classification algorithms provided better performances: LBP (Local Binary Pattern) and LPQ (Local Phase Quantization) [6]. They were tested on the four LidDet 2011 datasets (Biometrika, Italdata, Digital and Sagem from the names of the sensors used to collect the images) and, whilst the results change depending on the considered dataset, these two algorithms always worked better than the others leading to a 12.25% error rate on average for LPQ and a 12.20% for LBP. These performances convinced us of the effectiveness of a textural analysis approach to liveness detection. But, because of the alternating success of the two algorithms, we were looking for something able to combine their qualities.

In this paper we propose the use of another texture classification algorithm, the BSIF (Binarized Statistical Image Features) [8]. It is a local image descriptor constructed by binarizing the responses to linear filters but, in contrast to previous binary descriptors, the filters are learnt from natural images using independent component analysis (ICA). The BSIF descriptor has two parameters: the filter size and the number of features extracted. Our experiments proved that, with a sufficient number of features, this algorithm clearly outperformed both LBP and LPQ.

Section 2 of this paper examine the details of the BSIF descriptor. Section 3 describe the datasets and the experimental protocol and show the results. Finally Section 4 concludes the paper.

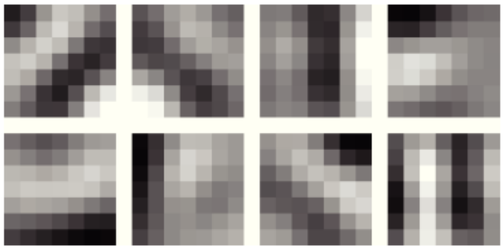

Figure 1: Learnt filters of size 9×9.

2. Fingerprint Representaion with Binarized Statistical Image Features

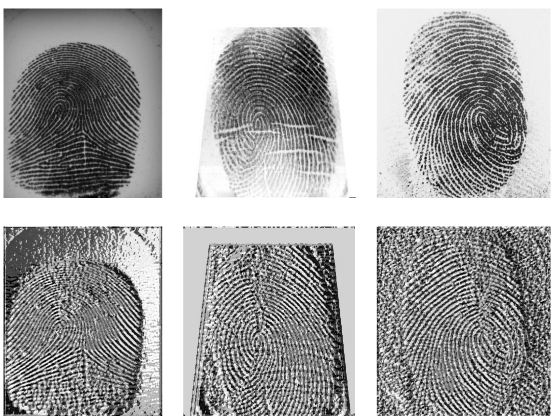

Figure 2: Some fingerprint images and corresponding BSIF codes.

Local image descriptors make the backbone of the current approaches for visual object recognition. The function of descriptors is to convert the pixel-level information into a useful form, which captures the most important image and video contents but is insensitive to irrelevant aspects caused by varying environment. In contrast to global descriptors which compute features directly from the entire image, local descriptors, which have proved to be more effective in real world conditions, represent the features in small local image patches.

Many popular local descriptors such as LBP [1] and LPQ [15] can be seen as statistics of labels computed in the local pixel neighborhoods through filtering and quantization. These methods describe each pixels neighborhood by a binary code which is obtained by first convolving the image with a manually predefined set of linear filters and then binarizing the filter responses. The bits in the code string correspond to binarized responses of different filters. These methods showed very good results in different computer vision problems [13].

For efficiently representing fingerprint images for liveness detection, we adopt a new local descriptor called BSIF (binarized Statisitcal Image features) which was recently proposed by Kannla and Rahtu for face recognition and texture classification [8]. Inspired by LBP and LPQ, the idea behind BSIF is to automatically learn a fixed set of filters from a small set of natural images, instead of using hand-crafted filters such as in LBP and LPQ. Our proposed approach for fingerprint representation consists of apply learning, instead of manual tuning, to obtain statistically meaningful representation of the fingerprint data, which enables efficient information encoding using simple element-wise quantization. Learning provides also an easy and flexible way to adjust the descriptor length and to adapt to applications with unusual image characteristics such as fingerprints.

To characterize the texture properties within each fingerprint sub-region, the histograms of pixels BSIF code values are then used. The value of each element (i.e. bit) in the BSIF binary code string is computed by binarizing the response of a linear filter with a threshold at zero. Each bit is associated with a different filter and the desired length of the bit string determines the number of filters used. The set of filters is learnt from a training set of natural image patches by maximizing the statistical independence of the filter responses [7].

Given an image patch X of size $l \times l$ pixels and a linear filter W_i of the same size, the filter response s_i is obtained by

$$s_i = \sum_{u,v} W_i(u,v)X(u,v) = w_i^T x,$$

where vectors w and x contain the pixels of W_i and X.

The binarized feature b_i is obtained by setting $b_i = 1$ if $s_i > 0$ and $b_i = 0$ otherwise.

The filters W_i are learnt using independent component analysis (ICA) by maximizing the statistical independence of s_i.

In our experiments, we used the set of filters provided by the authors of [8] and learnt from a set of 13 natural images. There are two parameters in the BSIF descriptor: the filter size l and the length n of the bit string. The filters W_i were learnt using different choices of parameter values, each set of filters was learnt using 50000 image patches. The filters obtained with $l = 9$, $n = 8$ are illustrated in Figure 1. Some fingerprint images and corresponding BSIF codes are shown in Figure 2.

3. Experimental results

3.1. Data sets and experimental protocol

All the algorithms were tested using the four datasets collected for the Second International Fingerprint Liveness

Detection Competition (LivDet 2011) by four optical sensors (Biometrika, Italdata, Digital Persona, Sagem) [16]. Each dataset is divided in two parts, one used to train a classifier and the other to test the classifier performances. Both part consist of around 1000 “live” and 1000 “fake” fingerprint images.

These fakes were created using the consensual method: a volunteer put his finger on a mould of plasticine like material, another material like gelatine or liquid silicon is poured over the mould. The result, after a certain time interval, is an artificial replica of the fingertip.

The classifier adopted in all our tests was a linear Support Vector Machine. For each algorithm we calculated the Equal Error Rate (EER) that is the value for which the percentage of misclassified live fingerprints (False Positive Rate) is equal to the percentage of misclassified fake fingerprints (False Negative Rate).

3.2. Proposed feature sets for comparison

As previously stated, the BSIF descriptor depends on two parameters: the filter window size and the number of bits that compose the binary code string. The selected number of bits determines the number of features extracted.

Results obtained for different combinations of those values have been investigated. For the sake of space we selected a combination of window size, (7x7), and features number (4096 corresponding to 12 bits) capable of good performances on all datasets and we compared the results with those of the LBP and LPQ algorithms. Since the feature extracted with the LBP were 54 and those extracted with LPQ were 256, in order to better figure out how much the feature number influence the performances, we also present the results obtained with window size 7x7 and both 6 and 8 bits. Using 6 bits we get a 64 features vector that is slightly larger than the LBP one whilst using 8 bits we get a 256 features vector just like the LPQ one.

3.3. Results

First, in Table 1, we present the EER values calculated for the BSIF with 8 bits (256 features) and a window size that change from 3x3 to 17x17 whilst, in Table 2, for the BSIF with a (7x7) window size as the bits number change from 5 to 12 (i.e. the number of features increase from 32 to 4096). It is clear that, while the best window size seems to change depending on the sensor, the error rate mostly decrease as increase the features number.

In Table 3 the EER values calculated for the BSIF with a (7x7) window size and 12 bits are compared with the state-of-the-art of fingerprint liveness detection: LPQ [8], LBP [8], Pores detection [9], Valleys wavelet [14] and Curvelet GLCM [11].

Results of our analysis are reported in Table 4 as EER values and presented in two different sets of figures where

Biometrika	Italdata	Digital	Sagem	
10.70	18.75	5.65	7.06	size 3x3
11.00	19.95	6.30	8.54	size 5x5
12.20	23.35	9.50	10.20	size 7x7
14.15	25.00	10.20	7.75	size 9x9
18.25	33.10	6.85	7.86	size 11x11
14.70	31.80	6.50	7.37	size 13x13
14.00	36.10	7.20	8.82	size 15x15
18.65	33.95	11.15	11.60	size 17x17

Table 1: Equal Error Rates for the Biometrika, Italdata, Digital and Sagem sensors calculated for BSIF at 8 bits and different window sizes.

Biometrika	Italdata	Digital	Sagem	
20.55	54.50	15.75	16.52	5 bits (32 feat.)
20.80	39.75	17.70	12.02	6 bits (64 feat.)
17.80	29.20	13.60	12.17	7 bits (128 feat.)
12.20	23.35	9.50	10.20	8 bits (256 feat.)
11.85	21.80	6.75	6.72	9 bits (512 feat.)
7.35	16.35	5.55	6.69	10 bits (1024 feat.)
7.80	13.75	4.40	5.83	11 bits (2048 feat.)
6.80	13.65	3.55	4.86	12 bits (4096 feat.)

Table 2: Equal Error Rates for the Biometrika, Italdata, Digital and Sagem sensors calculated for BSIF with a 7x7 window sizes and different bits numbers.

we plotted the ROC curves (one image for each sensor). In Figure 3, 4, 5, 6 we show the ROC curves of the BSIF with a (7x7) window size and 12 bits compared with those of LPQ and LBP. It is evident the superiority of the BSIF algorithm with the partial exception of the Italdata ROCs where its curve is nearly equaled by that of the LPQ. In Figure 7, 8, 9, 10, the comparison is between the LPQ, LBP and the BSIF with a (7x7) window size and both 8 and 6 bits (that, as stated early, are the two bits values that lead to a features numbers similar to those of LPQ and LBP).

Results clearly show that the BSIF, with a large enough bits number, outperform the other algorithms, but they also

Biometrika	Italdata	Digital	Sagem	
6.80	13.65	3.55	4.86	BSIF (12b)
14.65	14.35	11.95	8.04	LPQ
10.95	18.95	10.55	8.35	LBP
27.35	28.75	35.85	41.59	Pores detection
29.00	23.65	13.05	32.47	Valleys wavelet
22.90	30.75	18.35	28.00	Curvelet GLCM

Table 3: Equal Error Rates for the Biometrika, Italdata, Digital and Sagem sensors calculated for BSIF (win7x7,12b), LPQ, LBP, Pores detection, Valleys wavelet and Curvelet GLCM.

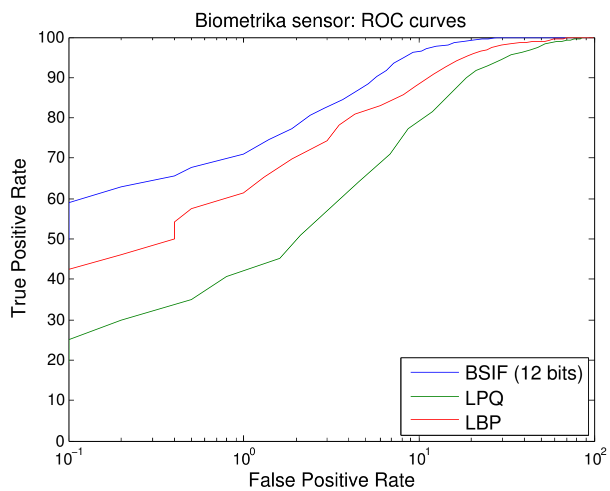

Figure 3: ROC Curves for Biometrika of the BSIF with a (7x7) window size and 12 bits compared with those of LPQ and LBP.

Bmk	Itd	Dgt	Sgm	mean	std dev	
6.80	13.65	3.55	4.86	7.22	4.49	BSIF(12b)
14.65	14.35	11.95	8.04	12.25	3.05	LPQ
12.20	23.35	9.50	10.20	13.81	6.46	BSIF (8b)
10.95	18.95	10.55	8.35	12.20	4.64	LBP
20.80	39.75	17.70	12.02	22.57	12.02	BSIF (6b)

Table 4: Equal Error Rates for the Biometrika, Italdata, Digital and Sagem sensors, mean EER and standard deviation calculated for BSIF (win7x7,12b), LPQ, BSIF (win7x7,8b), LBP and BSIF (win7x7,6b)

show that a bits reduction greatly decrease the algorithm performances. As a matter of fact the BSIF with 6 bits is always the worse. The BSIF with 8 bits is comparable to both LPQ and LBP with the exception of the Italdata where it loses more than 4 point with respect to the LBP and so much as 9 with the LPQ. Finally the BSIF with a 7x7 window and 12 bits (4096 features) proved to be significantly better than the others. With the Italdata (again) the percentage gain is less than one if compared to the LPQ, but for the other datasets there is always an improvement of several points.

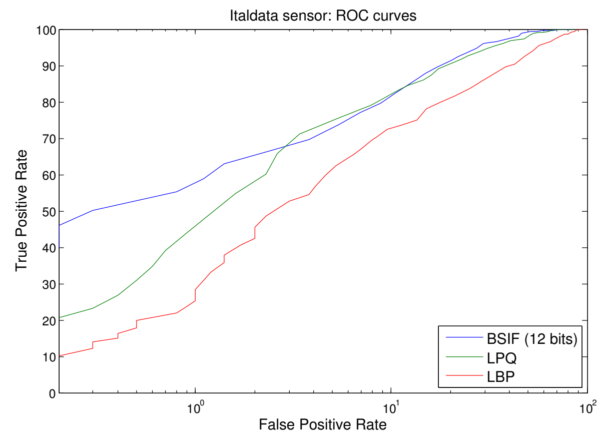

Figure 4: ROC Curves for Italdata of the BSIF with a (7x7) window size and 12 bits compared with those of LPQ and LBP.

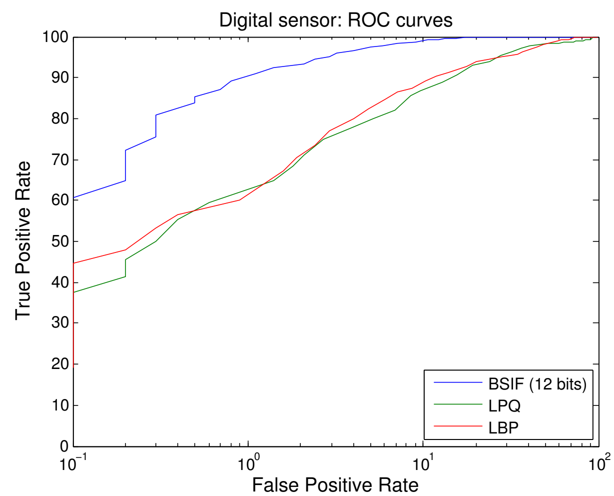

Figure 5: ROC Curves for Digital Persona of the BSIF with a (7x7) window size and 12 bits compared with those of LPQ and LBP.

The Italdata uniqueness is due to the fact that the images (Figure 11) collected with that sensor seems too clean and "less natural" than those collected with the others datasets. That's probably the reason why for the BSIF filters, automatically learned from natural images, the task is more dif-

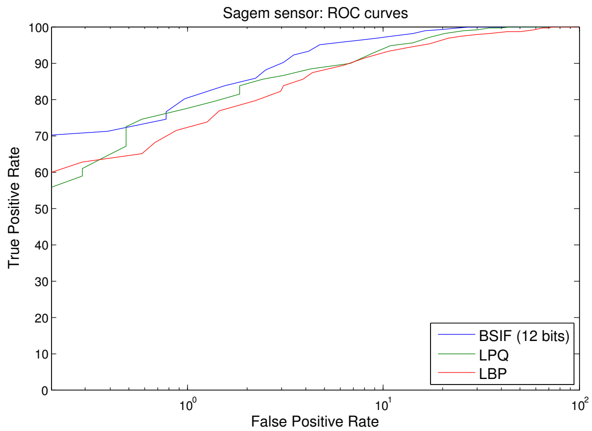

Figure 6: ROC Curves for Sagem of the BSIF with a (7x7) window size and 12 bits compared with those of LPQ and LBP.

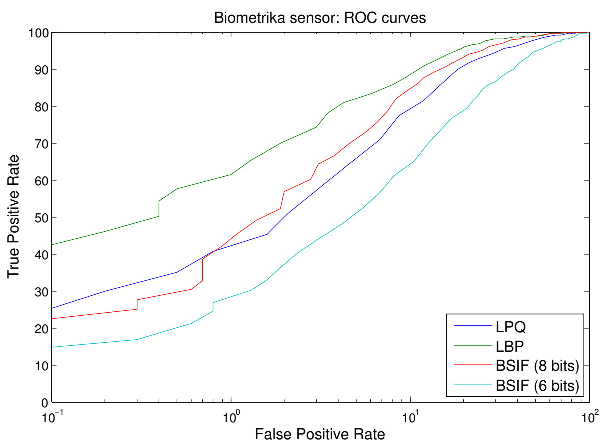

Figure 7: ROC Curves for Biometrika of the BSIF with a (7x7) window size and 8 bits compared with those of LPQ and of the BSIF with a (7x7) window size and 6 bits compared with those of LBP.

ficult. Besides the visible blurring effect in the images is the reason of the better performances of a blur invariant algorithm like LPQ that almost equate the BSIF with 12 bits.

Though the results are very promising and clearly improve the state-of-the-art, the main issue seems to be the feature number and a future work should include an thorough analysis and selection of those feature. However the classification times grows from 0.2674 seconds for BSIF with 6 bits to 0.5030 for BSIF with 8 bits to 13.0287 for BSIF with 12 bits Since those are the average times required to classify around 2000 fingerprints, the classification time required for a single image using LIBSVM [2] and Matlab [10] is low enough even using 4096 features.

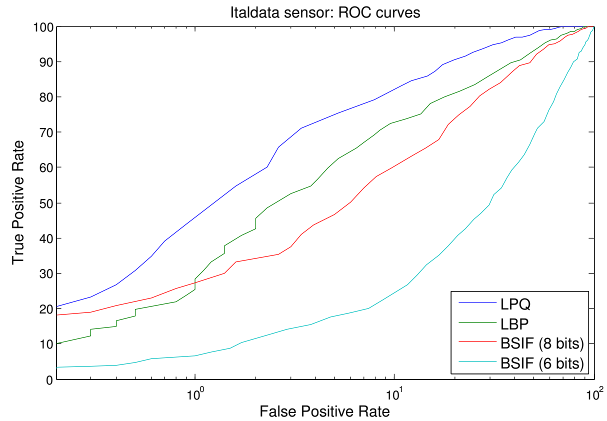

Figure 8: ROC Curves for Italdata of the BSIF with a (7x7) window size and 8 bits compared with those of LPQ and of the BSIF with a (7x7) window size and 6 bits compared with those of LBP.

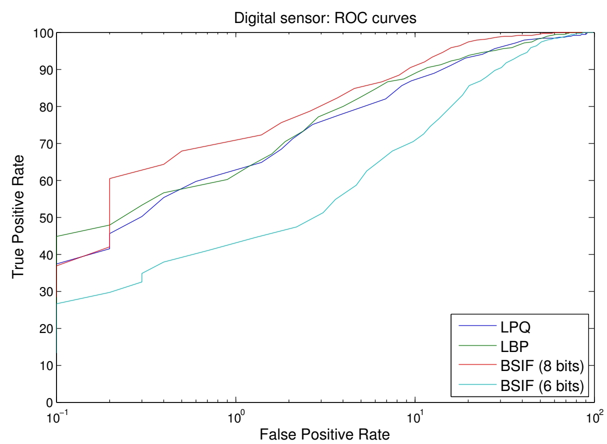

Figure 9: ROC Curves for Digital Persona of the BSIF with a (7x7) window size and 8 bits compared with those of LPQ and of the BSIF with a (7x7) window size and 6 bits compared with those of LBP.

4. Conclusions

In this paper we introduced the use of BSIF, a textural analysis algorithm, in fingerprint liveness detection. We test it on the four LivDet 2011 datasets with more than promising results. There are still some open issues: how to find the right window size, the bits number or, alternatively, how to perform a features selection since the best results are obtained extracting a large number of them.

A future work should be focused on filters. We used a set of predefined filters learned from a small set of natural images. With the use of filters learned from a set of images acquired from a particular sensor (and then customized for

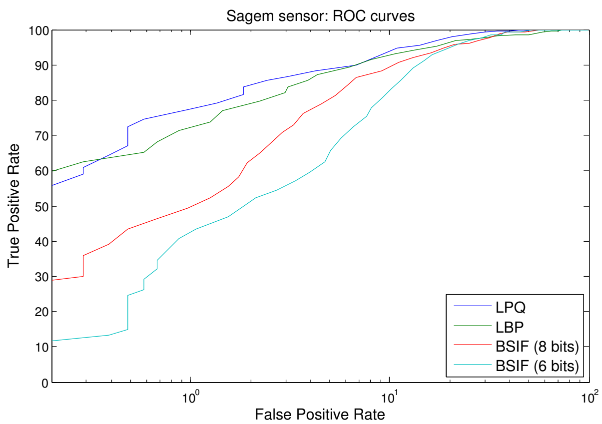

Figure 10: ROC Curves for Sagem of the BSIF with a (7x7) window size and 8 bits compared with those of LPQ and of the BSIF with a (7x7) window size and 6 bits compared with those of LBP.

Figure 11: Some fingerprint images collected with the Italdata sensor.

that sensor) the results might be further improved.

5. Acknowledgements

This work was partly supported by the Tabula Rasa project, 7th FP of the European Union (EU), grant agreement number: 257289.

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