Experimental Results on the Feature-level Fusion of Multiple Fingerprint Liveness Detection Algorithms

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ABSTRACT

The aim of fingerprint liveness detection is to detect if a fingerprint image, sensed by an electronic device, belongs to an alive fingertip or to an artificial replica of it. It is well-known that a fingerprint can be replicated and standard electronic sensors cannot distinguish between a replica and an alive fingerprint image. Accordingly, several countermeasures in terms of fingerprint liveness detection algorithms have been proposed, but their performance is not yet acceptable. However, no works studied the possibility of combining different feature sets, thus exploiting the eventual complementarity among them. In this paper, we show some preliminary experiments on feature-level fusion of several algorithms, including a novel feature set proposed by the authors. Experiments are carried out on the datasets available at Second International Fingerprint Liveness Detection Competition (LivDet 2011). Reported results clearly show that multiple feature sets allow improving the liveness detection performance.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms, Measurement, Security

Keywords

Biometrics, Fingerprint Liveness Detection, Pattern Recognition

1. INTRODUCTION

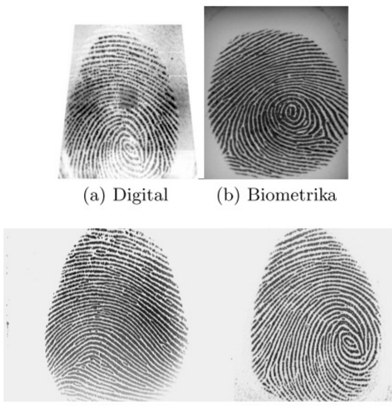
Biometrics are physical (fingerprints, face, iris) or behavioural (gait, signature) human characteristics that allow to identify a person univocally [1]. Since the importance of admitting people to enter a facility, access privileged information or even cross a border, biometric systems are considered to be more reliable for the person recognition than traditional methods based on PINs and passwords.

A biometric system is a pattern recognition system that acquires biometric data from an individual by an electronic device, extracts a features set from that data, compares these features against those stored in a database and performs a decision on the basis of the comparison result. [1]

Fingerprints are the most used, oldest and well-known biometric traits [2]. Performance of a fingerprint verification system is considered very high, beside the use of iris, and probably will further increase thanks to the very active research around this important field. However, fingerprints can be forged [3]. It is possible to create an artificial replica through several methods and using several materials, and the related images can be indistinguishable from alive ones (see for example Figures 1 and 2).

Therefore, the development of liveness detection techniques has been proposed to estimate if a fingerprint image is coming from an alive person or from a replica [4]. It is based on the principle that additional information can be obtained from the data acquired by a standard verification system, in order to detect the liveness degree of the given fingerprint.

To this aim, hardware-based systems use additional sensors to gain measurements directly from the finger of the person [4], whilst the software-based ones use image processing algorithms to gather information from the collected fingerprint image [4, 5, 6, 7, 8, 9, 10, 11, 12]. These systems classify images as either live or fake.



(a) Digital (b) Biometrika

(c) Italdata (d) Sagem

Figure 1: Examples of live fingerprints acquired with the 4 sensors.

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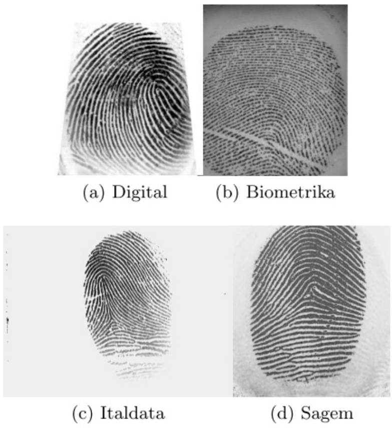

Figure 2: Examples of fake fingerprint acquired with the 4 sensors.

In this paper, we focus our attention on the software-based approaches, which are cheaper than hardware-based. In fact, they require additional and invasive hardware to measure the liveness from the fingertip of people. Instead, software-based must detect liveness from features extracted from the fingerprint images captured by the sensor. In other words, the liveness detection problem is treated as a pattern recognition problem, where a set of features must be selected in order to train an appropriate classifier.

Several fingerprint liveness detection algorithms have been proposed so far, but none of them clearly showed his superiority with respect to the others. The main problem is due to the difficulty of training appropriately a liveness detector, since fake fingerprint images can derive from replicas made up of a wide spectrum of materials, and it is practically impossible to cover this range; moreover, each algorithm has its own rationale. To the state-of-the-art, we can consider liveness measurements based on the live fingerprint characteristics, as the perspiration or the ridge-valley consistency [4]. On the other hand, other liveness measurements are based on the hypothesis that the fabrication process leads to significant modifications, due to the elastic deformation of the replica, the presence of artefacts, the loss of details [4]. From this point of view, no paper tried to exploit these basic differences, which could be pointed out by concatenating the feature vectors provided by each algorithm.

This is the goal of the present paper, which proposes a first experimental investigation on several feature sets at the state-of-the-art, and also proposes a novel one based on the local phase quantization extracted from the fingerprint image. Experiments are carried out on the four data sets of the second edition of the International Fingerprint Liveness Detection Competition [5] (LivDet2011).

This paper is organized as follows. Section 2 briefly describes the investigated algorithms, and the novel one introduced by the authors. Section 3 shows the experimental results. Section 4 concludes the paper.

2. FINGERPRINT LIVENESS DETECTION ALGORITHMS

2.1 State-of-the-art

Fingerprint liveness detection algorithms can be 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 artefacts during the fake production. Actually, this distinction is not rough, and the live-based class easily smooths on the fake-based one.

In the following, we briefly describe the eight most recent algorithms for extracting liveness measurements (or features). A first survey of fingerprint liveness detection approaches can be also found in [4].

Local Binary Patterns (LBP). They were first employed for two-dimensional textures analysis and excellent results were obtained due to their invariance with respect to grey level, orientation and rotation. The LBP algorithm extracts certain uniform patterns corresponding to micro-features in the image. The histogram of these uniform patterns occurrence is capable of characterize the image as it combines structural (it identify structures like lines and borders) and statistical (micro-structures distribution) approaches [6].

Pores detection (pores). Since the pores presence in live fingerprints determines the perspiration effect, the pores detection algorithm analyzes pores distribution in order to discriminate between fake and live fingerprint images. By scanning the image along the fingerprint ridges[7] it extracts the pores number and the average distance between pores.

Power spectrum. Coli *et al.* [8] analyzed fingerprints images in terms of high frequency information loss. In the artificial fingerprint creation, the ridge-valley periodicity is not altered by the reproduction process but some micro-characteristics are less defined. Consequently, high frequency details can be removed or strongly reduced. It is possible to analyze these details by computing the image Fourier transform modulus also called power spectrum.

Whilst the previous algorithms can clearly be associated to live-based ones, the following algorithms are based on the Wavelet analysis of the fingerprint image according to different rationales, and can provide both live-based and fake-based features.

Wavelet energy signature. Wavelet decomposition of an image [9] lead to the creation of four sub-bands: the approximation sub-band containing global low frequency information, and three detail sub-bands containing high frequency information. The image is decomposed in 4 levels using 3 different wavelet filters (Haar, Daubechies and Biorthogonal) and the approximation image is not considered, hence the sub-bands number is $3 \times 4 = 12$.

Ridges wavelet. After his extraction, a fingerprint skeleton can be used as a mask to obtain the gray level values along the ridges and these values are united into a signal. A wavelet multiresolution decomposition is applied to that signal with seven decomposition levels [10].

Valleys wavelet. In this case the skeleton of the valleys is obtained. As for the ridges wavelet analysis, the skeleton is used as a mask to extract a signal representing the gray level values along the valleys. A wavelet multiresolution decomposition is applied to that signal with seven decomposition levels [11].

Curvelet. The Curvelet waves [12] transform partitions curves into a collection of ridge fragments and then uses ridgelet transform to represent each of them. It is very efficient for representing edges and other singularities along curves due to its high directional sensitivity and its high anisotropy. We consider two different curvelet signature:

- **Curvelet energy signature**. The energies of the 18 sub-bands are measured by computing means and variances of curvelet coefficients.
- **Curvelet co-occurrence signature (curvelet GLCM)**. For each of the 18 sub-bands, the Gray Level Co-occurence Matrix (GLCM) is calculated together with 10 corresponding features.

Among the above eight feature sets, we selected four representative approaches: LBP, pores, valleys wavelet, and curvelet GLCM.

In the next Section, we present a novel feature set extracted by local phased quantization of the fingerprint image.

2.2 Feature set based on the LPQ of the fingerprint image

Due to the loss of information occurring during the fabrication process, a fingerprint image coming from an artificial replica can be considered as a "blurred" fingerprint, due to stretch of ridge and valleys, the deformation of the material, the pressure of the attacker on the sensor. This can be shown in Fig. 3, where several specific details of a live and the corresponding fake image are reported. These details points out that the appearance of the fake fingerprint appears as a blurred one, with respect to the live image.

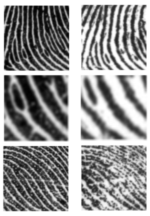

Figure 3: Zoom of a detail from live images (right), and fake images (left), correspondent to the live ones, that points out some "blurring" effects from the live to the corresponding replica.

The Local Phase Quantization (LPQ) is a blur insensitive texture classification method [13]. LPQ can be used successfully in fingerprint liveness detection as well, because it is able to represent all spectrum characteristics of images in a very compact feature representation, thus avoiding redundant or blurred information. LPQ could point out this fact, by its intrinsic blur insensitive representation. In other words, LPQ could point out the spectrum differences between a "live" fingerprint and a "fake" one.

A 2-D convolution between the original image $f(\mathbf{x})$ and the point spread function (PSF) of the blur $h(\mathbf{x})$ may express the image blurring $g(\mathbf{x})$. The vector $\mathbf{x}$ represents the coordinates (x, y). In the frequency domain: $G(\mathbf{u}) = F(\mathbf{u}) \cdot H(\mathbf{u})$, where $\mathbf{u}$ is the frequency and $G(\mathbf{u})$, $F(\mathbf{u})$, and $H(\mathbf{u})$ are discrete Fourier transforms (DFT). By considering the phase of the spectrum: $\angle G = \angle F + \angle H$.

If the PSF is centrally symmetric, $\angle H \in \{0, \pi\}$ as the Fourier transform H is always real and, usually, its shape is close to a Gaussian or a sinc function, hence H is positive at low frequency values. In that frequency interval, $\angle H = 0$ and $\angle G = \angle F$ proving that the phase is a blur invariant.

For every pixel $\boldsymbol{x}$, the local spectra is computed, using a short term Fourier transform (STFT) in the local neighborhood N_x, defined by a rectangular window function ω_R):

$$F(\mathbf{u}, \mathbf{x}) = \sum_{\mathbf{y}} f(\mathbf{y}) \omega_R(\mathbf{y} - \mathbf{x}) e^{-j2\pi \mathbf{u}^T \mathbf{y}} \tag{1}$$

This is a blur-insensitive representation, with four low frequency components: $\mathbf{u}_1 = [a, 0]^T$, $\mathbf{u}_2 = [0, a]^T$, $\mathbf{u}_3 = [a, a]^T$, $\mathbf{u}_4 = [a, -a]^T$, only if a is small enough to satisfy $H(u_i) > 0$. For each point x:

$$\mathbf{F}(\mathbf{x}) = [F(u_1, \mathbf{x}), F(u_2, \mathbf{x}), F(u_3, \mathbf{x}), F(u_4, \mathbf{x})] \tag{2}$$

Given the vector $\mathbf{G}(\mathbf{x}) = [Re\{\mathbf{F}(\mathbf{x})\}, Im\{\mathbf{F}(\mathbf{x})\}]$, from his j-th component g_j:

$$q_j = \begin{cases} 1, & \text{if } g_j \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

These eight binary coefficients can be written in the form of an integer value between 0 and 255:

$$F_{LPQ}(\mathbf{x}) = \sum_{j=1}^{8} q_j 2^{j-1}$$

An histogram, represented as a 256-sized feature vector, is then derived from all of these values (one for every pixel of the image).

A rotation invariant version of LPQ is obtained by considering that, given a rotation matrix $\boldsymbol{R}_\theta$, the Fourier transform of a rotated function is the Fourier transform of the original function rotated by $\boldsymbol{R}_\theta$. Therefore, using a circular Gaussian window, the coefficients of the local spectra (1) on a radius r around the point $\boldsymbol{x}' = \boldsymbol{R}_\theta \boldsymbol{x}$ are calculated at frequencies $\boldsymbol{v}_i = r[cos(\phi_i) sin(\phi_i)]^T$, with $\phi_i = 2\pi i/M$ and $i = 0, ..., M-1$.

From vector $\boldsymbol{V}(\boldsymbol{x}) = [F(v_0, \boldsymbol{x}), ..., F(v_{M-1}, \boldsymbol{x})]$, it is obtained $\boldsymbol{C}(\boldsymbol{x}) = Im\{\boldsymbol{V}(\boldsymbol{x})\}$ and then the characteristic orientation $\xi(x) = \angle b(x)$ is extracted from the complex moment:

$$b(x) = \sum_{i=0}^{M-1} c_i e^{j\varphi_i} \tag{4}$$

Instead of (2), the oriented frequency coefficients are used:

$$F_\xi(\boldsymbol{u}, \boldsymbol{x}) = \sum_{y} f(\boldsymbol{y}) \omega_R(R_{\xi(x)}^{-1}(\boldsymbol{y} - \boldsymbol{x})) e^{-j2\pi \boldsymbol{u}^T R_{\xi(x)}^{-1} \boldsymbol{y}}$$

Thus obtaining the rotation invariant LPQ, which has been used in this paper.

3. EXPERIMENTAL RESULTS

3.1 The LivDet2011 data sets

The Second International Fingerprint Liveness Detection Competition (LivDet) has been held in 2011, and results have been published in [5]. It has been organized by the University of Cagliari, Italy, and the Clarkson University, USA.

The competition employed four data sets for testing the performance of algorithms submitted by participants. In particular, the four LivDet 2011 datasets consist of images acquired with four different devices: Biometrika, Digital Persona, Italdata and Sagem. There are 4000 images for each of these devices, 2000 live images and 2000 fake images.

All the fake fingerprints have been created with the consensual method, by following these steps: the volunteer releases his fingerprint on a mould of plasticine or silicon-like material; the chosen material is poured or applied over the mould and after a certain time interval, this cast is removed from the mould, and can be used as fingerprint replica. Each replica in sensed by the sensor, that provide a "fake fingerprint image".

Spoof materials used were gelatine, latex, PlayDoh, silicone and wood glue for Digital Persona and Sagem; gelatine, latex, liquid silicon, silicone and wood glue for Biometrika and Italdata (400 of each of 5 spoof materials in both cases).

Each dataset of 4000 images per scanner was divided into two equal parts, training and testing. The first part had to be used to train the algorithm, and the second part to test them on independent data. In this paper, we followed the protocol of LivDet2011 [5].

3.2 Performance of individual algorithms

The fingerprint liveness system we adopted is sketched in Fig. 4. As the fingerprint image is submitted, it is processed by one or more algorithms of liveness features extraction. The corresponding feature sets are concatenated and a classifier (in our case, a Support Vector Machine with linear kernel) is trained on images belonging to the training set. The output is a liveness score, interpreted as the probability of the live class given the feature set(s).

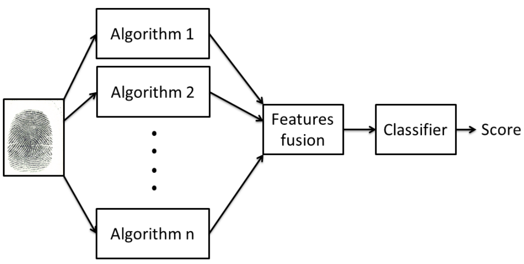

Figure 4: The fingerprint liveness detection system adopted in this paper.

First of all, we tested the performance of individual feature sets. Results are reported in Table 1, in terms of Equal Error Rate (EER), that is, the operational point for which percentage of misclassified fake fingerprints (False Positive Rate, FPR) is equal to the percentage of misclassified live fingerprints (False Negative Rate, FNR). This operational point is obtained on the basis of classification threshold applied to the liveness score. In this paper we also used the term True Positive Rate (TPR), defined as $TPR = 1 - FNR$, in order to plot the ROC curves of the adopted algorithms. ROC curves plot the points FPR, TPR for each value of the threshold.

Table 1 clearly shows that feature sets based on the proposed local phase quantization (LPQ) but also local binary patterns (LBP) exhibit the best EER, on overall. Among the five investigated algorithms, pores detection and valleys analysis (based on wavelet) exhibit the worst performance, but they can be more or less effective depending on the data set. From Tabel 1 we may observe that: similar performance does not mean strong correlation among algorithms. Thus, even LBP and LPQ may exhibit a certain complementarity. On the other hand, where we observe a relevant performance difference, the real advantage of the worst algorithm must be observed only on the basis of the set of images which are correctly classified and that are wrongly classified by the best algorithm.

3.3 Fusion of multiple fingerprint liveness detectors

In this Section, we show the performance of algorithms by combining up to three different feature sets, from the best to the worst one according to the related EER value.

Table 2 reports in each row the EER achievable by progressively concatenating two and three feature vectors, for each LivDet2011 data set. The addition of third feature set appears to be significant only in the case of the Sagem data set. In other cases, EER does not exhibit significant decrease. Therefore, feature level fusion seems to make sense only when no more than two feature vectors are joined. However, concluding that a third feature vector cannot bring information could be premature. In fact, we must consider that the ratio between the total number of features and samples available in the related feature space, by simple concatenation, strongly increases. This is known as the curse of dimensionality, which has an impact on the system performance. In order to avoid this problem, a feature selection/reduction criterion could be applied.

From another point of view, we can verify that, thanks to this fusion, images wrongly classified by individual algorithms have been actually recovered. This is evident in Fig. 5 and Fig. 6, where we reported some live and fake images in the case of Biometrika data set (similar cases have been found on the other data sets). Worth noting, these images clearly show that the increase of the fake images quality, as the decrease of the live images quality, contributes to the overlap between fake and live classes, thus more information is necessary to correctly associate each image. Since LivDet 2011 data sets are made from fake fingerprints collected by the consensual method, experiments on latent fingerprints should be done in order to further understand the benefits and limits of current approaches.

Figs. 10-**??** show the ROC curves by concatenating up to three feature sets (the case of more than three feature sets has been removed for sake of clarity). The saturation effect which may be hypothesised from Table 2 is here more evident. This clearly show that it is useless to join a large number of feature sets. The complementarity among such feature sets, if any, must be exploited in other ways. The drop of performance, noticeable in some cases, also suggest that certain feature sets may contain redundant or noisy in-

Table 1: **EERs on the four LivDet 2011 datasets related to the individual feature sets.**

	Biometrika	Italdata	Digital	Sagem
LPQ	14.65	14.35	11.95	8.04
LBP	10.95	18.95	10.55	8.35
pores	27.35	28.75	35.85	41.59
valleys wavelet	29.00	23.65	13.05	32.47
curvelet GLCM	22.90	30.75	18.35	28.00

Table 2: EERs achievable by progressively concatenating two and three feature sets, for each LivDet2011 data set, are reported in Subtable 1. Correspondent feature sets are given in Subtable 2. For example, an EER equal to 7.70% has been obtained on the Biometrika data set by concatenating feature sets (1) and (2), namely, LBP and LPQ ones.

Subtable 1. Feature sets	(1)	(1)+(2)	(1)+(2)+(3)
Biometrika	10.95	7.70	7.65
Italdata	14.35	12.80	12.90
Digital	10.55	8.65	5.55
Sagem	8.04	7.07	6.83
Subtable 2. Feature sets	(1)	(2)	(3)
Biometrika	LBP	LPQ	curvelet GLCM
Italdata	LPQ	LBP	valleys wavelet
Digital	LBP	LPQ	valleys wavelet
Sagem	LPQ	LBP	curvelet GLCM

(a) one (b) two (c) three

Figure 5: Examples of fake fingerprint that required one, two or three joint feature sets for being correctly classified. It is worth to notice that more feature sets are required as the quality of fake images increases.

(a) one (b) two (c) three

Figure 6: Examples of live fingerprint that required one, two or three joint feature sets for being correctly classified. It is worth to notice that more feature sets are required as the quality of live images decreases.

formation, which confirms their bad performance when used individually. Despite this evidence, Figs. 10 helps in drawing some important observations about the current state-of-the-art on fingerprint liveness detection:

- current algorithms, individually, does not exhibit a performance satisfying enough to be integrated into a fingerprint verification system, especially when working at very crucial operational point, for example when $FPR = 1\%$, where it is evident that the correspondent TPR is still too low;
- despite above fact, the proposed LPQ appears as the best one, whose performance is comparable with that of LBP, strongly better than other ones;
- in general, the performance of fake-based algorithms appears to be better than that of live-based ones;
- the feature-level fusion of fingerprint liveness detection algorithms may help, but only at a certain extent. This means that the feature set to be joined must be carefully selected, and the curse of dimensionality must be taken into account. While doing these passages, the performance of individual algorithms must be considered. Feature selection does not mean only the selection of feature sets, but also the eventual application of the feature reduction algorithm (*e.g.*, by PCA), in order to enhance the complementarity among the initial feature sets.

4. CONCLUSIONS

In this paper, the feature-level fusion of several fingerprint liveness detection algorithms has been done, beside the proposal of a novel algorithm, based on the local phase quantization of the fingerprint images.

If the proposed approach has shown a performance level comparable with that of the best state-of-the-art algorithm, based on local binary patterns (LBP), the feature-level fu-

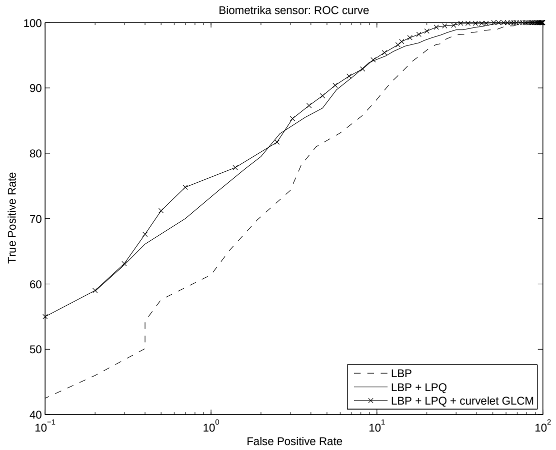

Figure 7: ROC curves on the LivDet2011 Biometrika data set, obtained by increasing the number of concatenated feature sets.

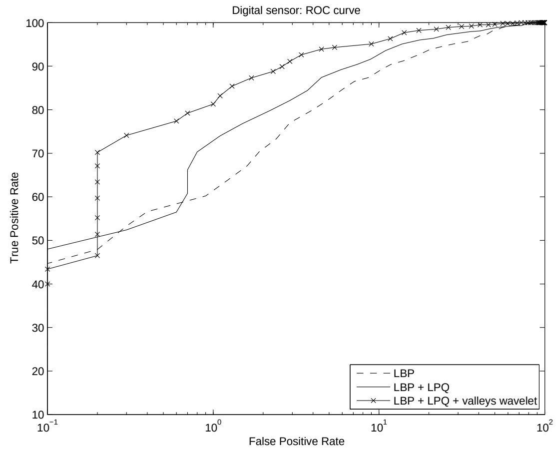

Figure 9: ROC curves on the LivDet2011 Digital Persona data set, obtained by increasing the number of concatenated feature sets.

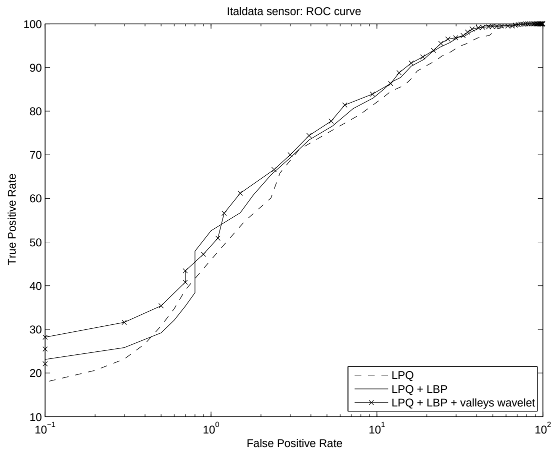

Figure 8: ROC curves on the LivDet2011 Italdata data set, obtained by increasing the number of concatenated feature sets.

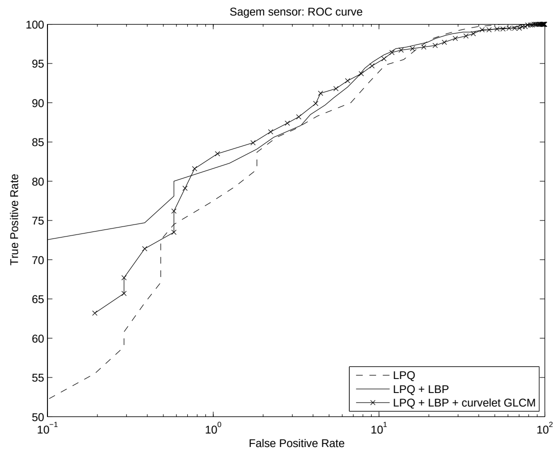

Figure 10: ROC curves on the LivDet2011 Sagem data set, obtained by increasing the number of concatenated feature sets.

sion of multiple fingerprint liveness detection algorithms appeared to be generally useful, but only at a certain extent. In other words, we obtained a strong performance improvement only by fusion of the best two individual algorithms. When concatenating more than two feature sets, we noticed a saturation effect and, in certain cases, a drop of the performance. This suggested the presence of redundant or noisy information, thus the selection of the feature sets to be combined must be done carefully, evaluating the size of each feature vector, the individual performance, and the real complementarity of them according to a preliminary analysis of a representative subset of data.

To sum up, we believe to have done another step ahead with respect to the state-of-the-art, by pointing out that current fingerprint liveness detection algorithms cannot be adopted individually, but their combination, carefully handled, can help in improving the performance, thus allowing their integration in current fingerprint verification systems.

5. ACKNOWLEDGMENTS

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