Fingerprint Liveness Detection by Local Phase Quantization

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Abstract

Fingerprint liveness detection consists in verifying if an input fingerprint image, acquired by a fingerprint verification system, belongs to a genuine user or is an artificial replica. Although several hardware- and software-based approaches have been proposed so far, this issue still remains unsolved due to the very high difficulty in finding effective features for detecting the fingerprint liveness. In this paper, we present a novel features set, based on the local phase quantization (LPQ) of fingerprint images. LPQ method is well-known for being insensitive to blurring effects, thus we believe it could be useful for detecting the differences between an alive and a fake fingerprint, due to the loss of information which may occur during the replica fabrication process. The method is tested on the four data sets of the Second International Fingerprint Liveness Detection Competition, and shows promising and competitive results with other state-of-the-art features sets.

1 Introduction

Fingerprint Liveness Detection has become an active research field in the last years, even thanks to international competitions that have raised the interests to this "cops-and-robbers"-like problem [1]. It is well-known that as the use of fingerprint verification systems increases, even the trial to deceive these systems increases too.

Specifically, the problem consists in attacking a fingerprint verification system by submitting a fake fingerprint to the electronic sensor. It has been showed that standard optical and capacitive sensors are not able to distinguish between an image coming from a "true" fingerprint and another from an artificial replica.

Therefore, it is necessary to provide novel means to detect the "liveness" of a fingerprint image. Software-based solutions, that is, algorithms which can provide such a detection, are the most interesting and challenging ones, because they do not employ additional, invasive, biometric measurements as that of the heartbeat or the blood pressure on the fingertip. On the other hand, the "liveness" must be assessed only by features extracted from images.

Several approaches have been proposed so far, but none of them have shown to reach an very low error rate [1, 2, 3, 4, 5]. Therefore, there is room for further improvements and methods proposals.

In this paper, we suggest the use of the Rotation Invariant Local Phase Quantization (LPQ in the following), which is used in image processing for insensitiveness to blurring effects [6]. In fact, we suggested in other works [3] that steps for providing fingerprint replica could bring to the loss of important information, but this information is difficulty detectable by visual inspection or even by a simple analysis of the fingerprint spectrum [3]. The simplicity of the feature extraction provided by LPQ, and the compact representation of the image spectrum, allows us to embed all spectrum information of the fingerprint in a very small feature vector, which can be easily adopted for the final classification according to the preferred approach (nearest neighbour, neural network and so on). This method is compared by experiments with the best methodology at the state-of-the-art (SOA), namely, the local binary pattern representation (LBP) [2], and show competitive and complimentary performance on the four data sets collected for the Second International Fingerprint Liveness Detection competition, held in 2011 [1].

Paper is organized as follow. We briefly describe the LPQ method in Section II. Experimental results are reported in Section III. Section IV concludes the paper.

2 The proposed method

The Local Phase Quantization (LPQ) is a blur insensitive texture classification method [6] that, in our opinion, can be used successfully in Liveness Detection, because it is able to represent all spectrum characteristics of images in a very compact feature representation, thus avoiding redundant or blurred information. The use of this algorithm represents a step-ahead with respect to our previous work where a simple spectrum analysis showed some benefits but was not effective enough to detect the fingerprint liveness [3]. Therefore, the main reason of proposing this approach is to point out the spectrum differences between a "live" fingerprint and a "fake" one. Since different fingerprint orientations may arise on a sensor surface, we adopt the rotation invariant extension of LPQ.

Image blurring $g(\mathbf{x})$ can be expressed by a 2-D convolution between the original image $f(\mathbf{x})$ and the point spread function (PSF) of the blur $h(\mathbf{x})$, where the vector $\mathbf{x}$ represents the coordinates (x, y). In the frequency domain, the convolution become the product: $G(\mathbf{u}) = F(\mathbf{u}) \cdot H(\mathbf{u})$, where $\mathbf{u}$ is the frequency and $G(\mathbf{u})$, $F(\mathbf{u})$, and $H(\mathbf{u})$ are discrete Fourier transforms (DFT). If we just consider the phase of the spectrum, we obtain the sum: $\angle G = \angle F + \angle H$.

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 $\boldsymbol{x}$, we compute the local spectra using a short term Fourier transform (STFT) in the local neighborhood N_x (defined by a rectangular window function ω_R), obtaining:

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

That 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 we can write:

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

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

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

We can write these eight binary coefficients in the form of an integer value included between 0 and 255 through:

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

From all of these values (one for every pixel of the image), we obtain an histogram that can be represented as a 256 features vector.

In the rotation invariant version of LPQ we take advantage of the fact 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 $\boldsymbol{R}_\theta$. Instead of a rectangular window, we use a circular Gaussian one and 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 the vector $\boldsymbol{V}(\boldsymbol{x}) = [F(v_0, \boldsymbol{x}), ..., F(v_{M-1}, \boldsymbol{x})]$, we calculate $\boldsymbol{C}(\boldsymbol{x}) = Im\{\boldsymbol{V}(\boldsymbol{x})\}$ and then we extract the characteristic orientation $\xi(x) = \angle b(x)$ from the complex moment:

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

Instead of (2), we use the oriented frequency coefficients:

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

If we apply a rotation, the position of the coefficients changes, but the 256-value histogram is the same (rotation invariant LPQ).

3 Experimental Results

We used the four data sets collected for the Second International Fingerprint Liveness Detection Competiion (LivDet11 [1]).

Each data set consists in 2,000 live and 2,000 fake fingerprints, collected by four electronic sensors (Biometrika, Sagem, Digital Persona, Italdata). Fake fingerprints have been provided by using the consensual method over more than fifty volunteers. Briefly, the consensual method is made up of the following steps:

- the volunteer release his fingerprint on a mould of plasticine- or silicon-like material;
- a liquid silicon rubber, gelatine, latex, is dripped over the mould;
- after a certain time interval, this cast in removed from the mould, and can be used as fingerprint replica.

According to the LivDet2011 protocol, we used the first 2,000 images for training the classifier, and the remaining 2,000 for testing the algorithms performance.

Adopted classifier is a linear Support Vector Machine. We reported the best results we obtained on the test set for each feature extraction algorithm.

We compared our results with four SOA features sets for fingerprint liveness detection: Power Spectrum [3], Pores Detection [4], Local Binary Pattern [2], and the best wavelet-based features, namely, the Curvelet-based ones [5]. Each algorithm is based on a different principle with respect to ours, expect for [3]. Due to the lack of space, we can't describe in detail each algorithm, but Pores Detection is based on localizing the third-level features from the fingerprint images, a very difficult task, whilst Local Binary Pattern and Curvelet are typical textural approaches, even if they extract this information in two different ways.

Table 1 reports the Equal Error Rate, that is, the error rate given by the threshold value for which the False Positive Rate (the percentage of misclassified live fingerprints) is equal to the percentage of the False Negative Rate (the percentage of misclassified fake fingerprints). It is evident the strong performance difference between LPQ (the proposed method) and LBP with respect to the other ones. The Curvelet transform exhibits an intermediate level of performance but can be less effective than using the Pores Detection method if these third-level feature are "easier" to locate.

Anyway, LPQ and LBP methods are concurrent in giving the best EER in all cases and finally exhibit the same average EER, even if LPQ allows a more robust average result due to the lower value of standard deviation.

This is confirmed by ROC curves reported in Figs. 1. LBP and LPQ overtake each other, depending on the sensor images. This suggests a possible complementarity among these methods. In order to see if this is confirmed at least by a trivial experiment, we computed the simple average among the outputs of SVMs trained separately on the four data sets, and get the relative EERs, reported in the last row of Table 1. Worth noting, the less is the performance difference, the more is the improvement obtained by fusion. This effect clearly shows that the complementarity among these algorithms exists and is worthy to be studied in depth.

4 Conclusions

In this paper, we proposed a novel features set based on a textural analysis of the images spectrum, named Rotation Invariant Local Phase Quantization, for fingerprint liveness detection.

Preliminary experiments on the four LivDet2011 dataset, showed promising results. In particular, our method has shown to be strongly competitive, and, more, complimentary, with the best feature set at SOA, namely, the one based on the local binary patterns.

Future work will include larger experiments on novel fingerprint images, and also a depth study about the complementarity between the proposed method and other ones at the state-of-the-art.

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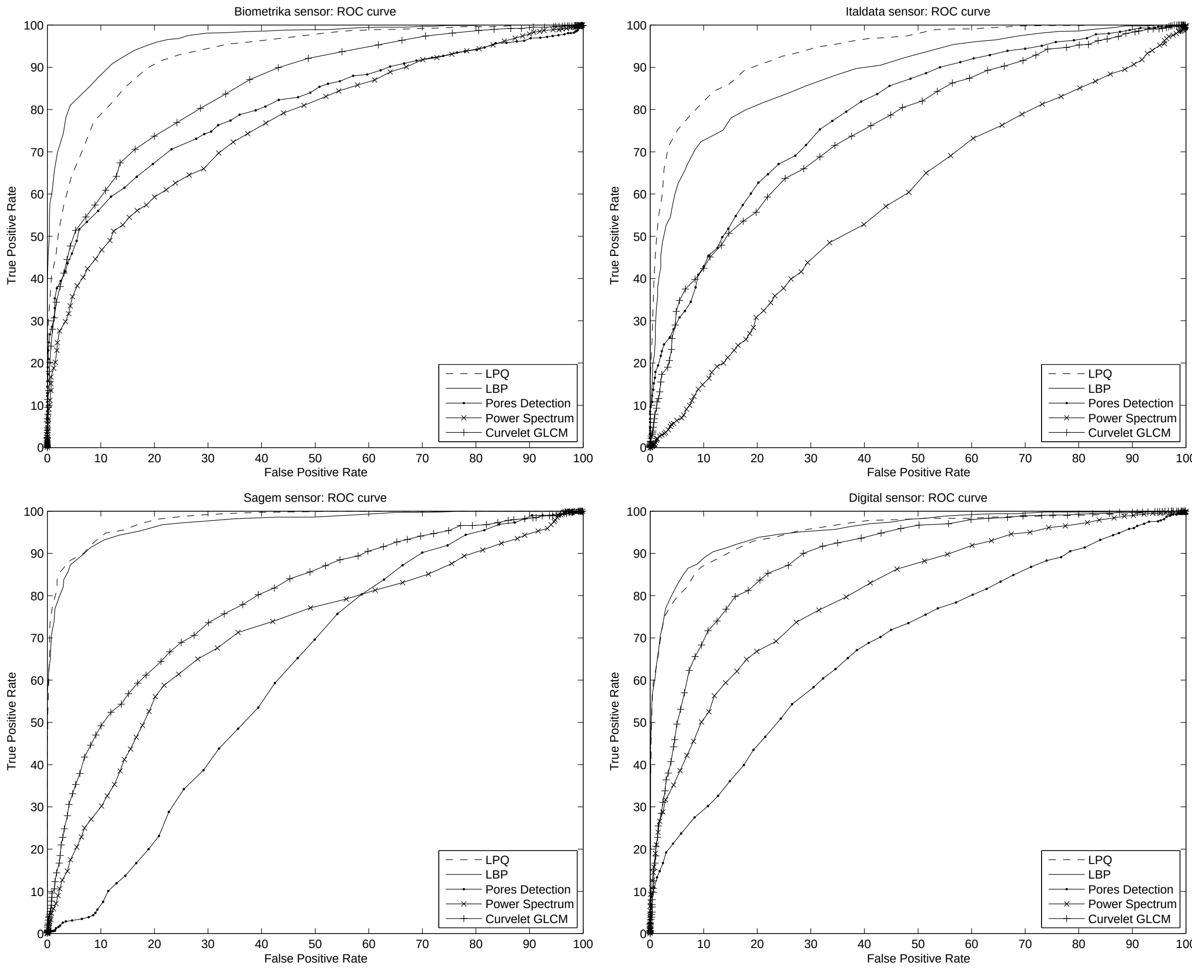

Figure 1. ROC curves of the four proposed algorithms on the four LivDet 2011 test images.

Table 1. Percentage EERs on the four LivDet 2011 test sets. Second column reports the number of features extracted by that algorithm, last column reports the average and standard deviation of EERs reported in columns 3-6. Last row reports the simple average among classifiers output related to LBP and LPQ features sets.

Feature set	Feat. number	Biometrika	Italdata	Digital	Sagem	EER mean (std. dev.)
LPQ (this paper)	256	14.7	**14.4**	12.0	**8.0**	12.3 (3.1)
LBP [2]	54	**11.0**	19.0	**10.6**	8.4	12.3 (4.6)
Pores Detection [4]	3	27.4	28.8	35.9	41.6	33.4 (6.6)
Power Spectrum [3]	9	31.2	43.5	26.8	32.1	33.4 (7.1)
Curvelet [5]	180	23.7	31.5	18.6	28.4	25.5 (5.6)
LPQ+LBP	310	10.4	13.2	8.0	5.3	9.2 (3.4)