Rapid and brief communication

Two-class fingerprint matcher

Alessandra Lumini, Loris Nanni*

DEIS, IEIIT – CNR, Università di Bologna, Viale Risorgimento 2, 40136 Bologna, Italy

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Abstract

We present a system for fingerprint verification that approaches the problem as a two-class pattern recognition problem. The features extracted by “FingerCode” are used to capture the ridge strength. This feature vector is then classified as genuine or impostor according to a novel approach to handle the fingerprint verification as a two-class problem. Moreover, we show that extracting the features from sub-images around the core permits to better represent the local information.

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1. Introduction

Various approaches of automatic fingerprint matching have been proposed in the literature. Fingerprint matching techniques may be broadly classified as being either minutiae-based, correlation-based or image-based (for a good survey see Ref. [1]).

Minutiae-based approaches first extract the minutiae from the fingerprint images; then, the matching between two fingerprints is made using the two sets of minutiae locations. The performance of minutiae-based techniques rely on the accurate detection of minutiae points and the use of sophisticated matching techniques to compare two minutiae sets.

In correlation-based fingerprint matching, the template and query fingerprint images are spatially correlated to estimate the degree of similarity between them.

Image-based approaches usually extract the features directly from the raw image, then, the decision is made using these features. The performance of image-based techniques is affected by non-linear distortions and noise present in the image. However, image-based approaches may be the only viable choice, for instance, when image quality is too low to allow reliable minutiae extraction. FingerCode [2] is a novel representation scheme that captures global and local features of a fingerprint in a compact fixed length feature vector. This technique makes use of the texture features available in a fingerprint to compute the feature vector by Gabor Filters.

In existing image-based approaches the authors give more significance to the effectiveness of the feature extraction rather than to the classification techniques. In this paper, we propose a new approach for fingerprint template creation and classification which may be used to improve the performance of an image-based matcher. We suggest a method to approach the fingerprint verification problem as a two-class pattern recognition problem (the two classes are genuine and impostor). Moreover, we propose to partition the region of interest around the core point in smaller sub-images, then to use the features extracted from each sub-image for training a different classifier, in order to make the system more robust to noise and distortions.

2. Fingerprint verification

The training stage proposed in this work consists of six modules:

- **Enhancement**: the image is enhanced using the technique described in Ref. [3];
- **Core detection**: the core is extracted by a Poincarè-based algorithm [1];
3. Template creation and classification

The verification stage proposed in this work consists of five modules: Enhancement; Core detection; Orientation computation; Feature extraction; Classification. The first four steps are performed as in the training stage, the Classification is detailed in Section 3.3.

3.1. Combining the features

The image-based approaches suffer from two types of distortions: noise, which is caused by the capturing device or by e.g. dirty fingers and non-linear distortions. Assuming that in most of cases distortions only affect one or more portions of the fingerprint, we suggest to partition the region of interest around the core point into 4 sub-images (the four quadrants of the Cartesian plane), such that the local information may be better represented (see Fig. 2).

The features are extracted once and then combined in several manner: we adopt the six combinations obtained by concatenating each couple of 2 feature vectors extracted from different sub-images (1° and 2° quadrant, 1° and 3° quadrant . . . ). Moreover, we reduce the dimensionality of each combined feature vector to k by Karhunen–Loève transform, in order to reduce the noise and the correlation among the features.

3.2. Training the classifier

We propose a novel approach to handle the fingerprint verification as a two-class problem. For each couple A and B of fingerprints of the training set,1 we calculate $e$ as the element-by-element difference between the respective feature vectors $a$ and $b$. The new feature vector $c$ is labelled as ’genuine’ if A and B belong to the same individual, as ‘impostor’ otherwise. A radial basis function-support vector machine classifier (SVM) is trained using the new feature vectors $c$. Since we have six feature vectors for each fingerprint, we create an ensemble of SVM classifiers, each trained on a different set of vectors (related to a combination of sub-images, as detailed in Section 3.1), and we combine the scores by the MAX rule.

3.3. Classification

Given a fingerprint X (with feature vector $x$) of an unknown individual claiming to be “Y” (whose stored feature vector is $y$), the verification can be performed by simply classifying the feature vector $d$ obtained as the element-by-element difference between $x$ and $y$.

In order to make this procedure more robust against slight errors in the core detection we compare the unknown fingerprint $x$ with all the original and extra-images generated for the claimed individual (say $y_1, \ldots, y_n$, see Section 2), selecting for classification $d_i = x - y_i$, where $i^*$ represent the index of the template which is more similar to the unknown fingerprint $x$:

$$i^* = \arg \min_{i=1,\ldots,n} \|x - y_i\|.$$ 

4. Experiments and discussion

The system performance was evaluated using images taken from FVC 2002 fingerprint dataset [4]. FVC2002 provided four databases: Db1, Db2, Db3 and Db4, each containing 8 fingerprint per 100 individuals; we discard 2 out of 8 impressions for each finger having an exaggerate displacement (the core is not present). We compare our methods (named 2Class) with the base FingerCode [2], improved by the same enhancement used in this paper for fair comparison. To validate our idea we also report the performance of a simpler two-class approach (Simple2Class) obtained using only one classifier trained directly by the FingerCode features (without the partition of the region of interest into 4 quadrants). The experiments were conducted

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1 To avoid a combinatorial explosion of combinations we do not insert the extra-images generated in the training set.
by using 2 training images per individual while the other 4 impressions are treated as the test images. For the performance evaluation we adopt equal error rate (EER) (Table 1).

Experimental results obtained on a large fingerprint database (FVC2002) show that:

(1) Deriving multiple “virtual” samples from each original sample in the training set, by perturbing the position of the core point, permits to obtain a more reliable system;

(2) Extracting the features from sub-images permits to better represent the local information (2Class obtains an EER lower than that obtained by Simple2Class);

(3) Our novel approach to handle the fingerprint verification as a two-class problem obtains a drastic reduction of the EER with respect to an image-based fingerprint verification method where classification is performed by a simple nearest neighbour classifier.

5. Conclusions

In this paper we introduced a new image-based fingerprint matcher whose performance is not still comparable to a minutia-based system, nevertheless dramatically outperforms the state-of-the-art of the image-based fingerprint matchers [2]. The main contribution of our system is a solution to consider the fingerprint verification problem as a two-class pattern recognition problem. We also studied the effects on the performance obtained by extracting the features from different sub-images around the core. We plan in the future to evaluate different methods to partition the fingerprint into sub-images and to select the most useful for classification.

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References


Further reading