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Pattern-based Fingerprint Matching Approach

Tudor Barbu, Mihaela Costin, Adrian Ciobanu

Abstract: We describe a pattern-based fingerprint recognition technique in this paper. First, some preprocessing operations performed on the fingerprint pattern are presented. Then we consider a fingerprint matching approach using a 2D Gabor filter bank and a supervised classification approach.

Keywords: fingerprint recognition, fingerprint pattern, region of interest, core point, 2D Gabor filter.

1 Introduction

Automatic fingerprint recognition represents the most used biometric authentication technique. The fingerprint recognition approaches are divided into two categories: minutiae based and pattern based techniques. We consider a pattern-based fingerprint recognition approach in this article [3,4].

The authentication algorithms based on this approach compare input fingerprint images with stored fingerprint patterns. This is done by registering digital fingerprint images based on a so called "core point" identified as a reference point in the pattern of fingerprints. Then the fingerprint image is globally represented by using Gabor filters, Fourier descriptors, Wavelet transforms or quantified co-sinusoidal triplets. Our approach is based on Gabor filter banks.

2 Fingerprint pattern preprocessing

Before doing any feature extraction, the fingerprint image must be preprocessed in order to improve it to a certain standard. We applied three techniques of preprocessing: normalization, segmentation and reference point detection.

By normalization we improve the contrast of the fingerprint image and this is done by distributing the range of gray levels in the image through the entire [0, 255] range [1]. So, if A is the initial grayscale image of dimension $[M \times N]$, then its normalized form A' is computed as:

$$A'(i,j) = 255 \cdot \frac{A(i,j)-\min(A)}{\max(A)-\min(A)}, \forall i \in [1,M], \forall j \in [1,N] \tag{1}$$

By segmentation we obtain the region of interest where the fingerprint is positioned inside the image, as fingerprint images can contain white regions around the real fingerprints. We did that by dividing the image in blocks of 8 by 8 pixels, calculating the percentage of gray level pixels as opposed to white pixels in each of these blocks and applying a threshold in order to qualify such a block as belonging to the region of interest (percentage higher than the threshold) or not.

The last preprocessing step is the detection of the reference point, or core point, of the fingerprint, which will be used as the center of the feature map corresponding to the fingerprint. It is defined as the point where the curvature of the fingerprint ridge is the most accentuated [2]. We constructed an orientation map of all ridges in the fingerprint image and then on this map we detect the pixels for which their orientation is more different than the one of its neighbors.

3 Gabor filter-based fingerprint matching

The 2D Gabor filtering is a known technique very useful in many areas of image processing and analysis. We used it here to extract global and local features of the fingerprint valleys and ridges. These filters capture local orientation and frequency information, very useful in characterizing fingerprint patterns [3]. In the case of an even symmetric 2D Gabor filter, we have:

$$G_{\theta_i,f,\sigma_x,\sigma_y}(x,y) = \exp\left(-\left[\frac{x_{\theta_i}^2}{\sigma_x^2} + \frac{y_{\theta_i}^2}{\sigma_y^2}\right]\right) \cdot \cos(2\pi f x_{\theta_i}) \tag{2}$$

where $x_{\theta_i} = x\cos\theta_i + y\sin\theta_i$, $y_{\theta_i} = y\cos\theta_i - x\sin\theta_i$.

The parameter f was determined in relation with the frequency of the ridges, which corresponds to the average distance between the ridges. For a 500 dpi image, the average distance between ridges is 8 pixels, hence we consider the value $f = \frac{1}{8} = 0.125$. We also set σ_x and σ_y to the same value 4 as a compromise between the robustness to noise and the filtering precision [4]. We have also considered 8 orientations for filtering, so $\{\theta_1, \dots, \theta_8\} = \{0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ, 112,5^\circ, 157^\circ\}$. The fingerprint image is filtered by convolution with the set of modeled 2D Gabor filters in (2) and for the 8 considered orientations.

Due to performance reasons, the results of the Gabor filtering (Fig.1, center) cannot be used directly as feature vectors. Instead, the Gabor filtered image is processed through a grid centered in the core point of the fingerprint [3,4]. This grid is composed of 10 by 10 cells, each cell having 16 by 16 pixels (see Fig.1, left).

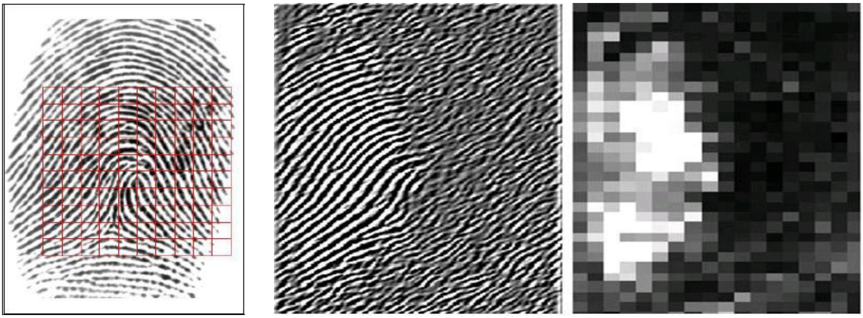

Figure 1. Rectangular grid applied to the fingerprint image (left), Gabor filtered fingerprint (center) and feature map (right)

For each rectangular cell we calculated the standard deviation of the Gabor filtered image, which corresponds to the local energy of the Gabor filter response. The collection of standard deviation values extracted from the grid form a feature map for the fingerprint, as we can see in Fig. 1, right. There are 8 such feature maps, one for each of the considered 8 orientations.

On the basis of these feature maps, we constructed a tridimensional feature vector for each fingerprint. So, if A is the analyzed fingerprint, then its feature vector is constructed as:

$$V(A)[x, y, i] = H_i(A), \forall i \in [1,8] \qquad (3)$$

where $H_i(A)$ is the feature map of fingerprint A corresponding to the θ_i orientation of the Gabor filter defined by (2). To measure the distance between such two feature vectors we used as a metric the sum of absolute differences between the vector components.

The pattern matching technique involves a supervised classification of these feature vectors with respect to the feature vectors corresponding to the already stored fingerprints patterns. The input fingerprints $\{A_1,\ldots, A_n\}$ are recognized using a training set of fingerprints

$\{\{Amp_j^i\}_{j=1,\ldots,n(i)}\}_{i=1,\ldots,N}$. The fingerprint A_j belongs to the fingerprint class $C_{ind(j)}$, where:

$$ind(j) = \arg\min_{i\in[1,N]} \frac{\sum_{n=1}^{n(i)} d(V(A_j), V(Amp_n^i))}{n(i)}, \forall j \in [1, n] \tag{4}$$

4 Conclusion

We have presented an approach to fingerprint recognition based on 2D Gabor filtering. The method was applied to a database of 140 images of 300 by 600 pixels including multiple images selected for each finger of 5 individuals. The experiments produced an authentication rate of over 80%.

Using a larger number of orientations for the Gabor filters can increase the recognition rate of the method at the expense of computational time. The complexity of the 2D Gabor filtering in one direction is of the order O(n), as it is normalization and segmentation, while the detection of the reference point has a complexity of O(n^2).

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Tudor Barbu[1], Mihaela Costin[2], Adrian Ciobanu[3]

[1,2,3]Institute of Computer Science Iaşi – Romanian Academy, Iaşi branch, Romania
E-mail: [1]tudbar@iit.tuiasi.ro, [2]mccostin@gmail.com, [3]a.ciobanu@upcnet.ro

[2]Institute of Computer Science Iaşi – Romanian Academy, Iaşi branch, Romania
E-mail: a.ciobanu@upcnet.ro