Synthetic Fingerprint-image Generation

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Abstract

This work introduces a novel method for the generation of synthetic fingerprint images. Gabor-like space-variant filters are used for iteratively expanding an initially empty image containing just one or a few seeds. A directional image model, whose inputs are the number and location of the fingerprint cores and deltas, is used for tuning the filters according to the underlying ridge orientation. Very realistic fingerprint images are obtained after the final noising-and-rendering stage.

1. Introduction

Since the 1950s, when the first algorithms for automated fingerprint recognition were developed by the U.S. Federal Bureau of Investigation (FBI), several efforts have been made to provide effective methods for forensic/civil applications and for a wide range of security tasks. Nowadays, the enormous interest aroused by electronic commerce on Internet and, more in general, by the need for reliable techniques to authenticate the identity of a living person in a broad range of applications has greatly intensified the research efforts towards the development of low cost fingerprint-based systems [1].

Although several algorithms have been independently developed by researchers both in academic and industrial environments, the main problems remain benchmarking and performance certification. In fact, testing a fingerprint recognition algorithm requires a large database of samples due to the small errors which have to be estimated [2]. For example, if an algorithm is quoted at 0.01% *FAR* (that is, the probability of falsely accepting an impostor is 1 in 10,000), then about 1,000,000 attempts of matching against impostor fingerprints are necessary to claim, with a 95% certainty, that the true error lies in the range [0.006%..0.014%]. Furthermore, once a database has been "*used*" (that is, third party algorithms have been tested and optimized on it) it will expire since for a successive fair testing stage a new unknown database is mandatory.

Gathering large databases of fingerprint images may be problematic due to the great amount of time (and money) required and due to the privacy legislation which in some countries prohibits the diffusion of personal information like fingerprints. The contest FVC2000 (Fingerprint Verification Competition) which will be held in conjunction with the 15th ICPR, provides some fingerprint databases to establish a common benchmark for academia and industry, but does not constitute a lasting solution since in a short time the benchmark will expire.

The main aim of this work is to propose a new method for the generation of synthetic fingerprint images, which can be used to create, at zero cost, large databases of fingerprints, thus allowing recognition algorithms to be simply tested and optimized. A further motivation is to better understand the rules involved in the biological process at the origin of fingerprints in nature. Finally, effectively modeling fingerprint patterns could also contribute to develop very useful tools for the inverse task, i.e. fingerprint feature extraction.

With the aim of robustly binarizing a gray-scale fingerprint image, Sherstinsky and Picard [3] proposed a complex method which employs a dynamic non-linear system called "M-lattice," which is based on the reaction-diffusion model first proposed by Turing in 1952 to explain the formation of animals' patterns such as zebra stripes. More recently, D. Kosz of the Polish company Optel sp. published some interesting results [4] concerning artificial fingerprint generation based on a novel mathematical model of ridge patterns and minutiae. Unfortunately, the author does not provide any technical details to protect the commercial exploitation of his idea. To the best of our knowledge, no other works in the literature concern the problem of synthetic fingerprint generation.

2. Fingerprint anatomy

A fingerprint is the representation of the epidermis of a finger. At a macroscopic analysis, a fingerprint is composed of a set of *ridge lines* which often flow parallel and sometimes produce local macro-singularities called *core* and *delta*, respectively. The number of cores and deltas in a single fingerprint is regulated in nature by some stringent rules; fingerprints are usually partitioned into five main classes (*arch*, *tented arch*, *left loop*, *right loop*, *whorl*) according to their macro-singularities (fig. 1).

The ridge-line flow can be effectively described by a structure called *directional map* which is a discrete matrix whose elements denote the orientation of the tangent to

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the ridge lines (fig. 2.b). Analogously, the ridge line density can be synthesized by using a *density map* (fig. 2.c).

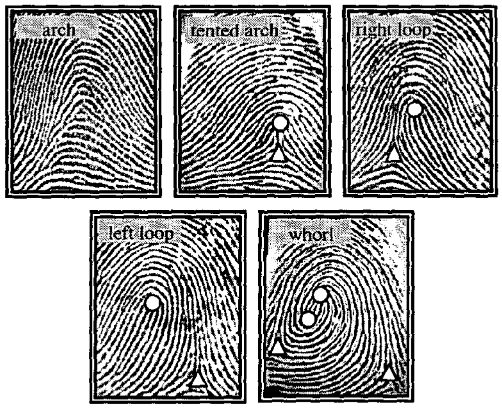
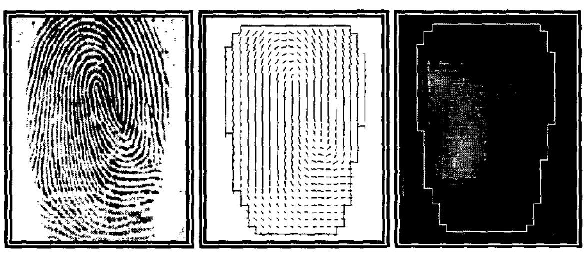


Fig. 1. One fingerprint for each of the five main classes: white circles denote loop singularities, whereas white triangles denote delta singularities.



a b c

Fig. 2. Figure 2.b reports the directional image of the fingerprint 2.a, whereas figure 2.c shows its local density map (the white blocks correspond to higher density regions).

At a finer analysis other very important features can be discovered in the fingerprint patterns. These micro-singularities, called ***minutiae*** or Galton characteristics, are essentially determined by the termination or the bifurcation of the ridge lines (fig. 3). Minutiae matching, which is essentially a point pattern matching problem, constitutes the basis of most of the automatic algorithms for fingerprint comparison.

3. Synthetic fingerprint generation

The generation method proposed in this paper sequentially performs the following steps:

1. Directional map generation
2. Density map generation
3. Ridge pattern generation
4. Noising and rendering

Fig. 3. A binarized portion of a fingerprint whose minutiae are highlighted.

Step 1, starting from the positions of cores and deltas, exploits a mathematical flow model to generate a consistent directional map. Step 2 creates a density map on the basis of some heuristic criteria inferred by the visual inspection of several real fingerprints. In step 3, the ridge-line pattern and the minutiae are created through a space-variant linear filtering; the output is a near-binary very clear fingerprint image. Step 4 adds some specific noise and produces a realistic gray-scale representation of the fingerprint.

4. Directional map generation

The orientation model proposed by Sherlock and Monro [5] allows a consistent directional map to be calculated from the position of the cores and deltas only. In this model the image is located in the complex plane and the orientation is the phase of the square root of a complex rational function with its singularities (poles and zeros) located at the same place as the fingerprint macro-singularities (cores and deltas). Actually, in nature the ridge-line flow is not only determined by the macro-singularities type and position, and a more sophisticated model should be considered [6]. Anyway, the Sherlock and Monro model constitutes a satisfactory starting point. Let $\mathbf{c}_i$ $i=1..n_c$ and $\mathbf{d}_i$ $i=1..\, n_d$ be the coordinates of the cores and deltas respectively; the macro-singularities number and position is not free, but a formal treatment about this is beyond the aim of this paper (refer to [5] for more details). The orientation O at each point $\mathbf{z}$ is calculated as:

$$O(\mathbf{z}) = O_0 + \frac{1}{2}\left[\sum_{i=1}^{n_d} arg(\mathbf{z}-\mathbf{d}_i) - \sum_{i=1}^{n_c} arg(\mathbf{z}-\mathbf{c}_i)\right]$$

where O_0 is the background orientation (we set O_0=0), and the function $arg(\mathbf{z})$ returns the argument of the complex number $\mathbf{z}$. Figure 4 shows some examples of directional maps generated according to this model. Unfortunately, arch type patterns, which do not contain any macro-singularities, are not supported, and must be considered apart. Anyway, this does not constitute a big problem since arch directional-map generation is straighforward: we use a sinusoidal function whose frequency and amplitude are changed to control the arch curvature and aspect.

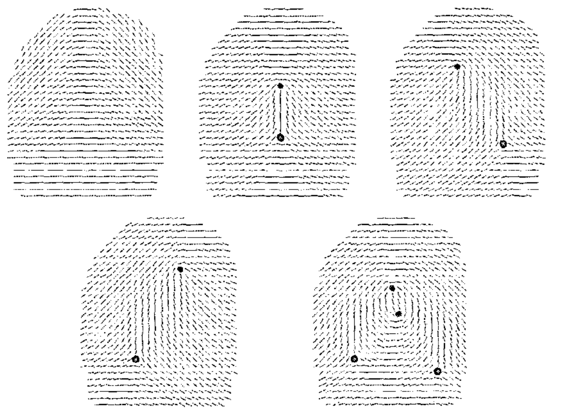


Fig. 4. An example of Arch, Tented Arch, Left Loop, Right Loop and Whorl directional maps as generated by the model adopted.

5. Density map generation

The visual inspection of several fingerprint images, leads us to immediately discard the possibility of generating the density map in a completely random way. In fact, we noted that usually in the region above the northernmost core and in the region below the southernmost delta the ridge-line density is lower than in the rest of the fingerprint. Our density-map generation method: 1) randomly selects a feasible overall background density; 2) slightly increases the density in the above-described regions according to the singularity locations; 3) randomly perturbs the density map and performs a local smoothing.

6. Ridge pattern generation

Given a directional map and a density map as input, a deterministic generation of a ridge-line pattern, including consistent minutiae, is not an easy task. One could try to fix a priori the number, the type and the location of the minutiae, and by means of an explicit model, generate the gray-scale fingerprint image starting from the minutiae neighborhoods and expanding to connect different regions until the whole image is covered. Such a constructive approach requires several complex rules and tricks to be implemented in order to deal with the complexity of fingerprint ridge-line patterns. A more "elegant" approach could be based on the use of a syntactic approach which generates fingerprints according to some starting symbols and a set of production rules. The method here proposed is very simple, but at the same time surprisingly powerful: by iteratively enhancing an initial image (containing one or more isolated spikes) through Gabor-like filters adjusted according to the local orientation and density, a consistent and very realistic ridge-line pattern "magically" appears; in particular, fingerprint minutiae of different types (terminations, bifurcations, islands, dots, etc.) are automatically generated at random positions. Formally, the filter is obtained as the product of a Gaussian by a cosine plane wave; a correction term is included to make the filter DC free [7]:

$$f(\mathbf{v}) = \frac{1}{\sigma^2} e^{-\frac{\|\mathbf{v}\|^2}{2\sigma^2}} \left(\cos(\mathbf{k} \cdot \mathbf{v}) - e^{-\frac{(\sigma\|\mathbf{k}\|)^2}{2}} \right)$$

where σ is the variance of the Gaussian and $\mathbf{k}$ is the wave vector of the plane wave. A graphical representation of the filter is shown in fig. 5. The parameters σ and $\mathbf{k}$ are adjusted using local ridge orientation and density. Let $\mathbf{z}$ be a point of the image where the filters have to be applied, then the vector $\mathbf{k}=[k_x, k_y]^T$ is determined by the solution of the two equations:

$$D(\mathbf{z}) = \sqrt{k_x^2 + k_y^2} \qquad tan(O(\mathbf{z})) = -\frac{k_x}{k_y}$$

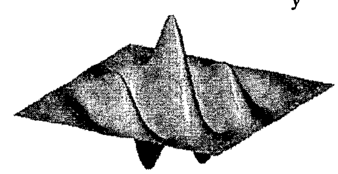


Fig. 5. A representation of the Gabor-like filter used in this work to create ridge-line patterns.

The parameter σ, which determines the bandwidth of the filter, is adjusted in the time domain according to $D(\mathbf{z})$ so that the filter does not contain more than 3 effective peaks (as shown in figure 5). The filter is then clipped to get a FIR filter. The filter should be designed with the constraint that the maximum possible response is larger than 1. When such a filter is applied repeatedly, the dynamic range of the output increases and becomes numerically unstable, but the generation algorithm exploits this fact. When the output values are clipped to fit into a constant range, it is possible to obtain a near-binary image. The above filter equation satisfies this requirement without any normalization.

Whilst one could reasonably expect that iteratively applying "striped" filters to random images would produce striped images, the generation of very realistic minutiae at random positions is somewhat unpredictable. During our experimentation we argued that minutiae primarily originate from the ridge-line disparity produced by local convergence/divergence of the orientation field and by density changes. In fig. 6, an example of the iterative ridge-line generation process is shown.

7. Noising and rendering

During fingerprint acquisition several factors contribute to deteriorating the original signal, thus producing a gray-scale noisy image: 1) irregularity of the ridges and their different contact with the sensor surface; 2) presence of small pores within the ridges; 3) presence of very-small-prominence ridges; 4) gaps and cluttering noise due to non-uniform pressure of the finger against the sensor or due to excessively wet or dry fingers.

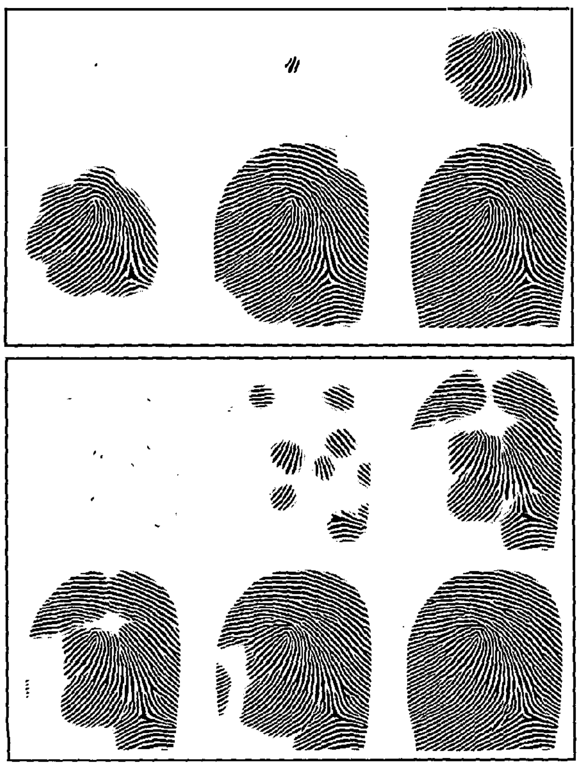


Fig. 6. The upper box shows some intermediate steps of an image-generation process starting from a single central spike. In the lower box the image has been initialized with a number of randomly located spikes.

Our noising and rendering approach sequentially performs the following steps:

1. Isolate the valley white pixels into a separate layer. This is simply performed by copying the pixels brighter than a fixed threshold to a temporary image.
2. Add noise in the form of small white blobs of variable size and shape. The amount of noise increases with the inverse of the fingerprint border distance.
3. Smooth the image over a 3×3 window.
4. Superimpose the valley layer to the image obtained.

Steps 1 and 4 are necessary to avoid an excessive overall image smoothing.

8. Conclusions and future work

In this work a novel method for generating synthetic fingerprint images is proposed.

Fig. 7. Two synthetic fingerprint images (first row) as obtained from the Noising and rendering step are compared with two real fingerprints captured with an on-line sensor.

Very-realistic fingerprints have been obtained (fig. 7); a demo program which generates fingerprints as described in this paper can be downloaded from http://www.csr.unibo.it/research/biolab/sfinge.html. We are currently working on improving some stages (especially directional map generation) and providing a method for generating different samples of the same finger, thus allowing benchmark databases to be completely-random generated.

Bibliography

[1] A. Jain, R. Bolle and S. Pankanti, *Biometrics - Personal Identification in Networked Society*, Kluwer Academic Publisher, 1999.

[2] J.L. Wayman, "Technical Testing and Evaluation of Biometric Devices", in A. Jain, et. al, *Biometrics - Personal Identification in Networked Society*, Kluwer Academic Publisher, 1999.

[3] A. Sherstinsky and R.W. Picard, "Restoration and enhancement of fingerprint images using M-lattice-A novel non-linear dynamical system", *Proc. 12th ICPR*, Jerusalem 1994.

[4] D. Kosz, "New numerical methods of fingerprint recognition based on mathematical description ...", in *Biometric in Human Service User Gruop Newsletter*, 15th issue, August 1999.

[5] B. Sherlock and D. Monro, "A Model for Interpreting Fingerprint Topology", in *Pattern Recognition*, v. 26, no. 7, 1993, pp. 1047-1095.

[6] P. Vizcaya and L. Gerhardt, "A Nonlinear Orientation Model for Global Description of Fingerprints", in *Pattern Recognition*, v. 29, no. 7, 1996, pp. 1221-1231.

[7] J.D. Daugman, "Complete discrete 2-d Gabor transforms by neural networks for image analysis and compression", *IEEE Trans. Acoustics, Speech, and Signal Processing*, v. 36, pp. 1169-1179, 1988.