

A Fingerprint Classification Technique Using Directional Images

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Abstract

We present a fast, automated, feature-based technique for classifying fingerprints. The technique extracts the singular points (delta and core points) in fingerprints obtained from directional histograms. The technique enhances the digitized image using adaptive clipping and image matching, finds the directional image by checking the orientations of individual pixels, computes directional histograms using overlapping blocks in the directional image, and classifies the fingerprint into the Wirbel class (whorl and twin loop) or the Lasso class (arch, tented arch, right loop, or left loop). The complexity of the technique is on the order of the number of pixels in the fingerprint image. The technique does not require iterations or feedback, and is highly parallel.

1. Introduction

Many fingerprint classification methods, such as Galton and Henry Classification [2], rely on point patterns in fingerprints which form ridges and bifurcations unique for each person. Point patterns belong to either the Wirbel class (whorl and twin loop) or the Lasso class (arch, tented arch, left loop, and right loop) [6,9,12] shown in Figure 1. Although this coarse classification is not enough to identify a fingerprint uniquely, it is useful in deciding when two fingerprints do not match [12]. We present an automated method for coarse fingerprint classification that determines the delta and core points using directional images and directional histograms.

2. Background

A *bifurcation* is the forking of one line into two or more branches. A *divergence* is the spreading apart of two

lines which have been running parallel or nearly parallel. *Type lines* are the two innermost ridges of the fingerprint which start parallel, diverge, and surround the pattern area. A *delta point* lies on a ridge at or in front of and nearest the center of the divergence of type lines. It is similar to a river delta. A *core point* is the approximate center of the finger impression. [10]

Traditional fingerprint images suffer from ink blotches, smudges, and poor contrast which hinders segmentation. Two segmentation-based methods for locating delta and core points use directional images for each pixel [4,5] and each block of pixels [6] but suffer from poor contrast [4,5] and loss of ridge details [6]. We essentially combine two previous techniques [4,6]. When we enhance contrast, however, we preserve ridge details by matching the enhanced and raw fingerprint images. We avoid thinning [8] and binarization.

3. Algorithm

We digitize fingerprints using a Cannon Powershot 600 CCD camera to obtain $M \times N$ (160 x 270) images. We classify the fingerprint using the algorithm below. The algorithm requires on the order of MN computations.

3.1. Preprocessing

We preprocess the raw gray-level fingerprint image to reduce distortion and enhance contrast. To reduce distortion, we adaptively clip the raw fingerprint image. At each pixel, we compute the average intensity value v in a 5×5 neighborhood. If the pixel value is less than v , then the pixel value is zero; otherwise, the pixel value remains unchanged. For enhancement, we average the clipped image and the raw fingerprint image to produce an $M \times N$ preprocessed image P .

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3.2. Directional Images

From the preprocessed image P , we compute an $M \times N$ directional image V that defines the orientations of pixels. We compute the orientation at each pixel $P(i,j)$ by sliding the 5×5 mask in Figure 2(a) over P where c is the center pixel $P(i,j)$. We look at the differences between $P(i,j)$ and $P(i_m, j_m)$ for $m = 1, 2, 3, 4$ where $i_m = \{i+2, i+2, i, i-2\}$ and $j_m = \{j, j+2, j+2, j+2\}$ in Figure 2(a). We use the minimum absolute difference to estimate the slope $V(i,j)$ of the orientation at $P(i,j)$:

$$V(i,j) = \min_m |P(i,j) - P(i_m, j_m)| \quad (1)$$

We compute a directional histogram for each $q \times q$ (5×5) block in V . For each block, we quantize the dominant direction to 0, 1, 2, or 3, which represent 0° , 90° , 45° , and 135° , respectively, as shown in Figure 2(b), to create an $M/q \times N/q$ reduced directional image S . The reduced size decreases the complexity of the rest of the algorithm.

3.3. Singular Points

Using the reduced directional image S , we determine the singular point candidates. If a point in S corresponds to a core point, then it has to satisfy the following inequality [6]:

$$90^\circ \leq (S(i,j) - S(i,j-1)) \leq 135^\circ \quad (2)$$

Since we do not use negative numbers, we compute (2) using a modulo operation. In order to obtain the relative delta points, we check the neighborhoods of $S(i,j)$ as follows:

$$\begin{aligned} S(i-1, j+1) &\leq S(i, j) < S(i+1, j+1) \\ S(i-1, j+1) &\leq 90^\circ \quad S(i+1, j+1) \geq 90^\circ \end{aligned} \quad (3)$$

If $S(i,j)$ satisfies (2), it is a possible core point. If it satisfies (3), it is a possible delta point.

Next, we eliminate the false singular points. For each delta point candidate at pixel $S(i,j)$, we check the adjacent horizontal and vertical pixels as shown in (4)

$$\begin{bmatrix} x & DP(i-1, j) & x \\ DP(i, j-1) & DP(i, j) & DP(i, j+1) \\ x & DP(i+1, j) & x \end{bmatrix} \quad (4)$$

$$\begin{aligned} DP(i, j-1) &\leq 90^\circ \text{ and } DP(i, j+1) > 90^\circ \\ DP(i+1, j) &\leq 45^\circ \quad 45^\circ \leq DP(i-1, j) \leq 135^\circ \end{aligned} \quad (5)$$

where $DP = S$. The x positions are not of interest. Candidates satisfying (3) and (5) correspond to true delta points.

For each core point candidate at pixel $S(i,j)$, we examine the 2×2 neighborhood to the Northwest, Southwest, Southeast, and Northwest corners to form directional core point matrices $H1$, $H2$, $H3$, and $H4$, respectively:

$$\begin{bmatrix} H1 & x & H3 \\ x & C(i, j) & x \\ H2 & x & H4 \end{bmatrix} \quad (6)$$

where $C = S$. The directional core point matrices are

$$H1 = \begin{bmatrix} C(i-2, j-1) & C(i-2, j-1) \\ C(i-1, j-2) & C(i-1, j-1) \end{bmatrix}$$

$$H2 = \begin{bmatrix} C(i-2, j+1) & C(i-2, j+2) \\ C(i-1, j+1) & C(i-1, j+2) \end{bmatrix}$$

$$H3 = \begin{bmatrix} C(i+1, j-2) & C(i+1, j-1) \\ C(i+2, j-2) & C(i+2, j-1) \end{bmatrix}$$

$$H4 = \begin{bmatrix} C(i+1, j+1) & C(i+1, j+2) \\ C(i+2, j+1) & C(i+2, j+2) \end{bmatrix}$$

Next, the dominant direction HD_n for each H_n matrix is found. Each H_n matrix has four entries and therefore four possible directions. In the case that two directions occur twice, i.e., there is a tie, then the core point is discarded. The dominant directions must satisfy

$$\begin{aligned} (HD1 \geq 90^\circ \text{ and } HD2 \leq 45^\circ) \text{ or} \\ (HD3 < 90^\circ \text{ and } 90 \leq HD4 < 180^\circ) \end{aligned}$$

If the core point is concave, then $H1$ must be left skewed and $H2$ must be right skewed. If $H3$ is right skewed and $H4$ is left skewed, the point must be convex. Concave and convex core points are kept.

3.4. Classification

If the fingerprint contains 0-1 delta points and 0-1 core points, then it is classified as Lasso, and Wirbel otherwise [12]. The Lasso class consists of arch, tented arch, right loop, and left loop:

- (1) If the fingerprint has 0 delta points or 0 core points, then the fingerprint is an arch;
- (2) Else if the core point and delta point are aligned in the vertical direction, then the fingerprint is an arch if the length between the core point and the delta point is less than 2.5 mm and tented arch otherwise;
- (3) Else if the core point is to the right of the delta point, then the fingerprint is a right loop.

(4) Else the fingerprint is a left loop.

The Wirbel class consists of whorl and twin loop:

(1) If there are exactly two core points and exactly two delta points, then the fingerprint is whorl if the two core points are aligned horizontally and the two delta points are aligned horizontally, and twin loop otherwise;

(2) Else the fingerprint is whorl.

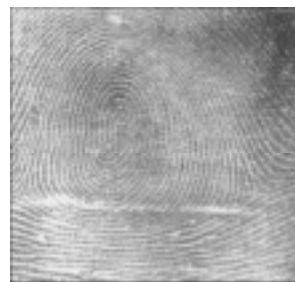
The classification of the fingerprint in Figure 3 is Wirbel class, whorl group.

Conclusion

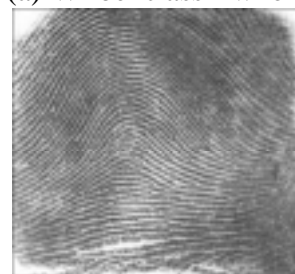
We introduce a fast fingerprint classification technique. Our method reduces processing time by removing the need for thinning and processing images in blocks. Our method increases resolution by determining directions for each individual and uses directional histograms to detect singular points. Our method outperforms similar featured-based fingerprint classification algorithms.

References

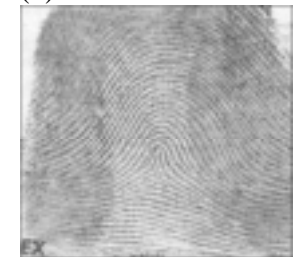
- [1] M. Ballan, *AFIS Archives Preparing and Methods of Directional Image Senior Project*, Electrical Engineering Dept., Yildiz Technical Univ., 80750 Istanbul, Turkey, Feb. 1997.
- [2] G. Ongun and U. Halici, "Fingerprint Classification Through Self-organizing Feature Maps Modified to Treat Uncertainties," *Proc. of the IEEE*, vol. 84, no. 10, pp. 1497-1512, Oct. 1996.
- [3] B. G. Sherlock, D. M. Monro, and K. Millard, "Fingerprint Enhancement By Directional Fourier Filtering," *IEE Proc. - Vision, Image, Signal Proc.*, vol. 141, no. 2, pp. 87-94, 1994.
- [4] B. M. Merthe, N.N. Murthy, S. Kapoor, and B. Chatterjee, "Segmentation of Fingerprint Images Using the Directional Image," *Pattern Recognition*, vol. 20, no. 4, pp. 429-435,
- [5] M. M. Merthe and B. Chatterjee, *Segmentation of Fingerprint Images—A Composite Method*, *Pattern Recognition*, vol. 22, no. 4, pp. 381-385, 1989.
- [6] V. S. Srinivasan and N. N. Murthy, "Detection of Singular Point in Fingerprint Images," *Pattern Recognition*, vol. 25, no. 2, pp. 139-153, 1992.
- [7] T. Akdogan, B. Sankur, H. Caglar, N. Yananli, and E. Anarim, *Fingerprint Images Smoothing and Characteristics Obtaining, Signal Processing and Applications Announcement Book, 1996*.
- [8] N. G. Bourbakis, "A Parallel Symmetric Thinning Algorithm," *Pattern Recognition*, vol. 22, no. 4, pp. 387-396, 1989.
- [9] *Turkish Police Security Organization Education Book*, Istanbul, Turkey.
- [10] *The Science of Fingerprints*, U.S. Department of Justice, Washington, D.C., 1974.
- [11] National Institute of Standards and Technology, http://www.nist.gov/srd/fing_img.htm.
- [12] K. Jaru and A. K. Jain, "Fingerprint Classification," *Pattern Recognition*, vol. 29, no. 3, pp. 389-404, 1996.



(a) Wirbel class - whorl



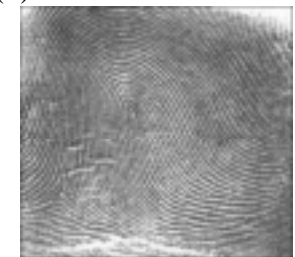
(b) Lasso class - arch



(c) Lasso class - tented arch



(d) Lasso class - left loop

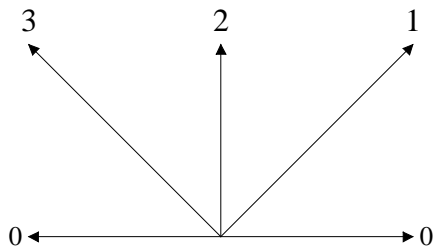


(e) Lasso class - right loop

Figure 1. Examples of Wirbel and Lasso fingerprints from the NIST database [11]. Twin loops are not distinguished as separate subgroups in the NIST database [12].

3		2		1
0		c		0
1		2		3

(a) 5 x 5 Direction mask

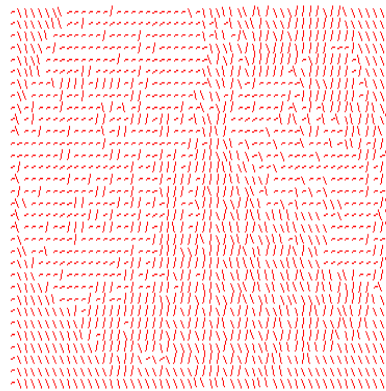


(b) Quantized directions

Figure 2. Directions For Filtering.



(b) 160 x 270 Preprocessed fingerprint image



(c) 32 x 54 Directional image of the preprocessed fingerprint.



(a) 164 x 278 Raw fingerprint image



(d) 32 x 54 Dominant directional component image

Figure 3: Applying directional filtering to fingerprint images.