Fingerprint Image Enhancement using Filtering Techniques

Shlomo Greenberg, Mayer Aladjem, Daniel Kogan and Itshak Dimitrov
Electrical and Computer Engineering Department,
Ben-Gurion University of the Negev, Beer-Sheva, Israel
Shlomog@ee.bgu.ac.il

Abstract

Extracting minutiae from fingerprint images is one of the most important steps in automatic fingerprint identification and classification. Minutiae are local discontinuities in the fingerprint pattern, mainly terminations and bifurcations. In this work we propose two methods for fingerprint image enhancement. The first one is carried out using local histogram equalization, Wiener filtering, and image binarization. The second method use a unique anisotropic filter for direct grayscale enhancement. The results achieved are compared with those obtained through some other methods. Both methods show some improvement in the minutiae detection process in terms of either efficiency or time required.

1. Introduction

Fingerprints are today the most widely used biometric features for personal identification. Most automatic systems for fingerprint comparison are based on minutiae matching [3]. Minutiae characteristics are local discontinuities in the fingerprint pattern which represent terminations and bifurcations. A ridge termination is defined as the point where a ridge ends abruptly. A ridge bifurcation is defined as the point where a ridge forks or diverges into branch ridges (Fig. 1). Reliable automatic extracting of minutiae is a critical step in fingerprint classification. The ridge structures in fingerprint images are not always well defined, and therefore, an enhancement algorithm, which can improve the clarity of the ridge structures, is necessary [4]. Most of the minutiae detection methods which have been proposed in the literature are based on image binarization, while some others extract the minutiae directly from gray scale images [5]. Concerning these two approaches, this work proposes two methods for fingerprint image enhancement. The first one is carried out using local histogram equalization, Wiener filtering, and image binarization. The second method use a unique anisotropic filter for direct grayscale enhancement. Section 2 addresses the main steps of our binarization approach. In Section 3 we suggest some modification to Hong's Gabor-based technique [4], and propose a fast direct grayscale fingerprint enhancement algorithm based on a unique anisotropic filter [2]. Section 4 presents the results of a comparative study of our approaches and the methods described in [4] and [5]. Finally, in Section 5 some conclusion are drawn.

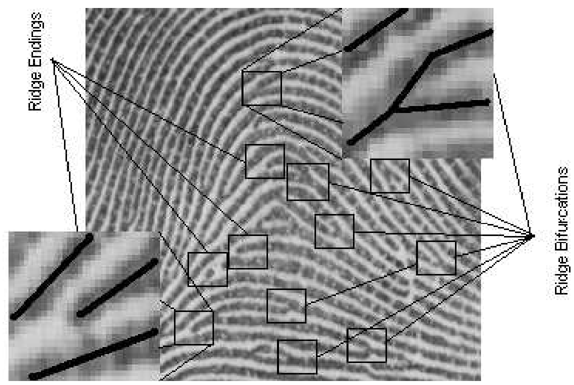

Figure 1. Examples of ridge ending and bifurcation

2. A binarization-based method

In some binarization-based approaches the binarization and thinning process are preceded by a smoothing operation, based on convolution with a gaussian mask [5], in order to regularize the starting image. We propose an enhancement process, which combine filters and noise reduction techniques for pre and post processing as well. The main stages of our proposed enhancement process (F) conducted on a binary ridge fingerprint images are shown in Fig. 2.

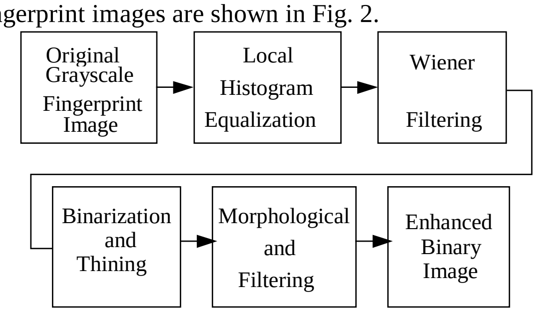

Figure 2. Filtering and binarization-based process

We use a local histogram equalization for contrast expansion and Wiener filtering for noise reduction. The binarization process is applied by adaptive thresholding based on the local intensity mean. Thinning is then carried out through the algorithm presented in [1], which provides good results on fingerprints. Finally morphological filtering is applied to eliminate artifacts in noisy regions and to fill some gaps in valid ridgelines.

2.1. Contrast enhancement

Histogram equalization defines a mapping of gray levels p into gray levels *q* such that the distribution of gray level *q* is uniform. This mapping stretches contrast (expands the range of gray levels) for gray levels near the histogram maxima. Since contrast is expanded for most of the image pixels, the transformation improves the detectability of many image features. The probability density function of a pixel intensity level r_k is given by:

$$p_r(r_k) = \frac{n_k}{n} \qquad (1)$$

where: $0 \le r_k \le 1$, $k = 0,1,...,255$, n_k is the number of pixels at intensity level r_k and n is the total number of pixels. The histogram is derived by plotting $p_r(r_k)$ against r_k. A new intensity s_k of level k is defined as:

$$s_k = \sum_{j=0}^{k} \frac{n_j}{n} = \sum_{j=0}^{k} p_r(r_j) \qquad (2)$$

We apply the histogram equalization locally by using a local windows of 11x11 pixels. This results in expanding the contrast locally, and changing the intensity of each pixel according to its local neighborhood. Fig. 3 (right) presents the improvement in the image contrast obtained by applying the local histogram equalization.

2.2. Wiener filtering noise reduction

We propose to use a pixel-wise adaptive Wiener method for noise reduction. The filter is based on local statistics estimated from a local neighborhood η of size 3x3 of each pixel, and is given by:

$$w(n_1, n_2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}\left(I(n_1, n_2) - \mu\right) \qquad (3)$$

where v^2 is noise variance, μ and σ^2 are local mean and variance, I represent the gray level intensity in $n_1, n_2 \in \eta$. The result of the wiener filtering is shown in Fig. 4 (left).

2.3. Binarization and thinning

The operation that converts a grayscale image into a binary image is known as binarization. We carried out the binarization process using an adaptive thresholding. Each pixel is assigned a new value (1 or 0) according to the intensity mean in a local neighborhood (13x13 pixels), as follow:

$$I_{new}(n_1, n_2) = \begin{cases} 1 \text{ if } I_{old}(n_1, n_2) \ge Local\ Mean \\ 0\ otherwise \end{cases} \qquad (4)$$

Thinned (one pixel thickness) ridgelines are obtained using morphological thinning operations (Fig. 4, right).

2.4. Post processing and binary filtering

We developed an algorithm to handle two typical kind of noise which appear in the thinned binary image: false ridgeline connections, and gaps within a true ridgeline. The false ridgeline connections are almost perpendicular to local ridge direction, and empirically found to be of length less than 10 pixels. Therefore, lines with similar features are automatically removed by our algorithm (Fig. 5, right). By matching pairs of ridgeline termination, gaps within a true continuous ridgeline are also eliminated.

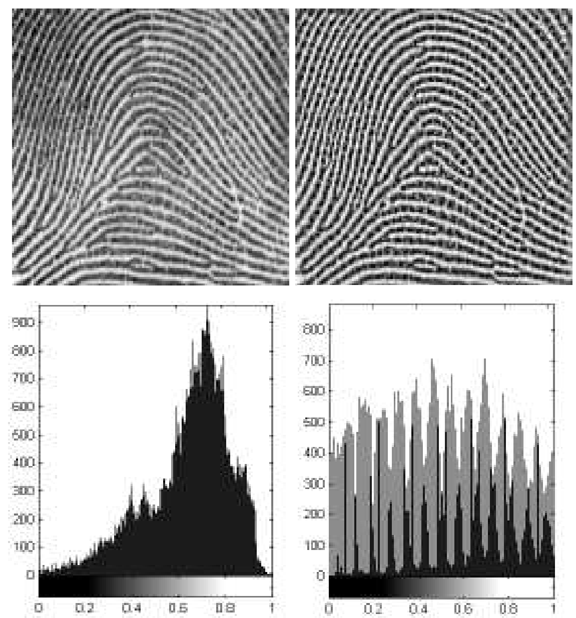

Figure 3. Histogram equalization: original image and its histogram (left) and after equalization (right)

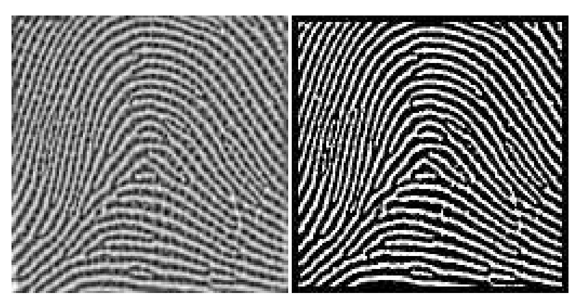

Figure 4. (left) Wiener filtering result using local neighborhood of 3x3 pixels and (right) Binary image

3. Direct gray scale enhancement approaches

Maio and Maltoni [5] proposed a technique, based on ridge line following, where minutiae are extracted directly from gray scale images. Hong [4] introduced a fast fingerprint enhancement algorithm based on a Gabor filter. In this section we propose a direct gray scale enhancement method, which has been stimulated by [4]. First we suggest some modification of the original algorithm [4], and then we propose a fast direct gray scale fingerprint enhancement based on an anisotropic filter.

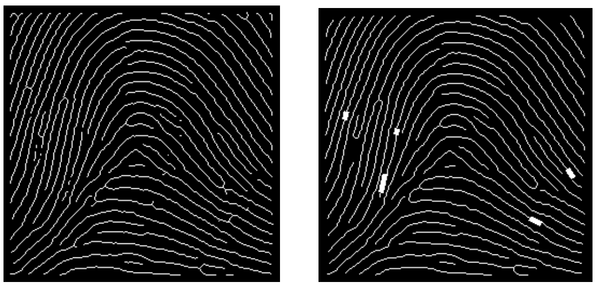

Figure 5. Post processing: (left) Thinned binary image (right) Removing false ridges and filling gaps

3.1. A modification of the Gabor-based algorithm

The main steps of Hong algorithm include normalization, local orientation estimation, local frequency estimation, and filtering [4]. A bank of Gabor filters, which is tuned to local ridge orientation and ridge frequency, is applied to the ridge and valley pixels in the normalized input fingerprint image to obtain an enhanced fingerprint image. The filters are used as bandpass filters to remove the noise and preserve true ridge/valley structures. We implemented this algorithm for comparison purposes introducing some modification. First, an alternative scheme, based on local gradient operations [5], is used for more precise orientation estimation. Fine tuning of some parameters in the original algorithm result in an efficient and more robust algorithm. The selection of the filter envelope standard deviations δ_x^2, δ_y^2, in some adapted orientation, involves a trade-off between robustness and spurious ridges [4]. In order to decrease the standard deviation in all directions perpendicular to the ridge direction we set the values of δ_x^2, δ_y^2 to 4.0 and 3.0 respectively. The new parameter settings create fewer spurious ridges and make the filter more robust to noise. For a given resolution, the value of the ridge frequency in a local neighborhood lies in a certain range [4]. By cutting down the valid frequency range, we avoid wrong estimation of the frequency in blocks which do not form a well-defined frequency. Finally, for better definition of the block's center, in the ridge frequency algorithm [4], we divide the normalized image into an odd block of size 15x15 instead of 16x16.

3.2. Enhancement with unique anisotropic filter

In this section we present a new direct gray scale method based on a unique anisotropic filter [2]. A structure adaptive anisotropic filtering technique is proposed by Yang [6] for image filtering. Instead of using local gradients as a means of controlling the anisotropism of filters, it uses both a local intensity orientation and an anisotropic measure to control the shape of the filter. We modified this anisotropic filter by shaping the filter kernel and applied it to fingerprint images[2]. The basic idea is that the kernel is allowed to be shaped or scaled according to local features within a given neighborhood. The filter kernel applied at each point x_0 is defined as follows [6]:

$$k(x_0,x)=\rho(x-x_0)\exp\left\{-\left[\frac{((x-x_0)\cdot n)^2}{\sigma_1^2(x_0)}+\frac{((x-x_0)\cdot n_\perp)^2}{\sigma_2^2(x_0)}\right]\right\} \qquad (5)$$

where n and $n_\perp$ are mutually normal unit vectors, and n is in parallel with the ridge direction. The shape of the kernel is controlled through $\sigma_1^2(x_0)$ and $\sigma_2^2(x_0)$, ρ satisfy the condition $\rho(x)=1$ when $|x|<r$, and r is the maximum support radius. We modified the filter to a band pass filter in order to adapt it to a fingerprint image [2]:

$$h(x_0,x)=-2+10*k(x_0,x) \qquad (6)$$

When a ridgeline edge is encountered the kernel is deformed into an ellipse with a major axis aligned in parallel with the edge (Fig. 6). Therefore, smoothing is performed along but not across the ridgeline. Our proposal is quite similar to the Gabor-based technique as both are using oriented filters. By applying our filter, only orientation information is required. In our enhancement algorithm we replaced the Gabor filter in [4] with the anisotropic filter [2], which eliminates the need to estimate local frequency information. This make our algorithm faster than [4].

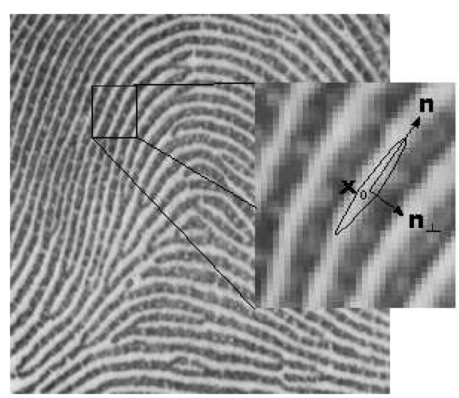

Figure 6. Controlling the shape of anisotropic filter

4. Experimental results

4.1. Comparison of binarization-based methods

Here we compare our binarization-based method with some other similar techniques. Maio [5] reports the average error percentage obtained with four different schemes (B,C,D,E) based on binarization and thinning. We refer to Maio [5,Fig.20], and use fingerprints from the same sample set in order to compare those four schemes to our binarization scheme, named F (see Section 2.1). The sample set is composed of 10 fingerprints taken from NIST, an FBI sample and through an opto-electronic device. Fig. 7 show the average error percentage obtained with the five different approaches. The results are reported in terms of undetected (dropped), non-existent (false), and type exchanged (exchanged) minutiae [5].

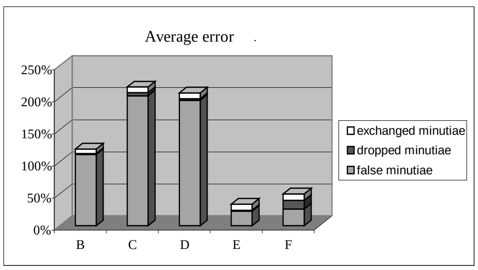

Figure 7. Comparison of 5 binarization-based scheme

4.2. Comparison of direct gray-scale methods

In this section we compare the enhancement results conducted on grayscale images by three different methods: the direct grayscale miniature detection (G) [5], the modified Gabor-based filtering (H) (see Section 3.1), and our anisotropic filtering (I) (Section 3.2). The results obtained with our binarization based approach (F) are also compared here. The graphics in Fig. 8 compare the average error percentage obtained with methods G, H, I, and F, for the same sample set as in 4.1. Fig. 9 shows some enhanced fingerprint images obtained with the Gabor-based algorithm [4] and our modification (Section 3.1), and with the anisotropic filter (Section 3.2).

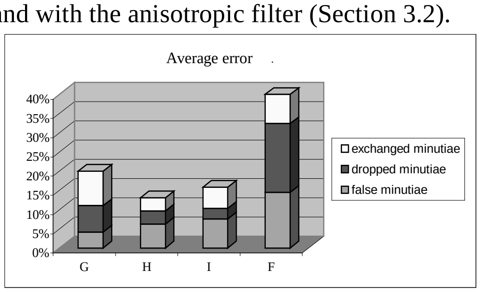

Figure 8. A comparison of 3 gray-scale approaches

5. Summary and Conclusions

The techniques based on direct gray scale enhancement perform better than approaches which require binarization and thinning as intermediate steps. The average error percentage, in terms of dropped, exchanged and false minutiae, as produced by our binarization approach F, is considerably lower than the errors produced by approaches B,C and D and comparable to the errors produced by approach E. The modified Gabor filter H performs better than the original scheme [4], especially for poor quality images with corrupted ridges and blocks with singular points (Fig. 9). The need for estimation of local frequency information, as conducted by Gabor-based filter, is eliminated by using our unique anisotropic filter. The proposed enhancement scheme is faster and efficient as well.

Figure 9. Enhancement results (clock-wise from up-left) : Original, gabor, modified gabor, and anisotropic filter

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