Logical Templates for Feature Extraction in Fingerprint Images

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Abstract

We present a novel approach for extraction of minutiae features from fingerprint images. The proposed approach is based on the use of logical templates for minutiae extraction in the presence of data distortion. A logical template is an expression that is applied to the binary ridge (valley) image at selected potential locations to detect the presence of minutia at these locations. It is adapted to local ridge orientation and frequency. We discuss the proposed technique in detail, and present experimental results on low-resolution images of various qualities.

1. Introduction

Reliable extraction of minutiae features in low resolution fingerprint images has been a difficult problem. This problem is complicated by the fact that fingerprint images can be substantially distorted due to several factors, such as noise, scars and small undesired artifacts. In order to deal with this problem, most of the approaches attempt to utilize the special nature of fingerprint images.

A feature extraction procedure generally consists of three steps: preprocessing, feature extraction and postprocessing. Preprocessing techniques attempt to capitalize on the special ridge-and-valley nature of fingerprint images for image filtering that is adapted to local orientation, and possibly local frequency (e.g., [1]). Feature extraction approaches are based on either: (a) thresholding, thinning and minutiae detection, or (b) ridge following in either gray scale image, or binary ridge image. The approaches based on thresholding and thinning are simple in principle, and some of the algorithms, like thinning, can be implemented in parallel. However, they tend to perform poorly in noisy and low contrast images. The ridge following approaches have the advantage that they can perform better on low contrast and noisy images. However, the algorithms are generally complex and nonadaptive. Representative feature extraction approaches can be found in the work of Coetzee and Botha [2], Mario and Maltoni [3], and Ratha et al. [4]. Postprocessing techniques attempt to rectify imperfections of the feature extraction process by utilizing model information such as minimum ridge length, and duality between ridge and valley minutia.

Motivated by the development of a distortion tolerant approach which can be computationally efficient and be implemented in parallel, we have developed an adaptive logical template based approach for feature extraction.

2. A New Minutiae Extraction Approach

The proposed algorithm consists of three steps: construction of orientation image, construction of ridge and valley images, and minutiae extraction. These steps are summarized as follows:

a) Construction of Orientation Image: The input image is first smoothed using a 5 x 5 Gaussian kernel of standard deviation 1.0. The Sobel operators are then applied to the smoothed image to estimate the gradient magnitude. The image is split into 16 x 16 blocks with one pixel overlap. For each block, the dominant orientation of the ridge pattern is obtained through least-squares estimation [5].

b) Construction of Ridge and Valley Images: The ridge (valley) image is a binary image, where the value of each pixel is one, if the pixel corresponds to a ridge (valley) pixel, and zero otherwise. Ridge and valley images are obtained as follows. The input image is first adaptively smoothed through guidance from the orientation image obtained in the first step. The purpose of this process is to eliminate most fine details such as islands, and merges "sub-ridge" sections that are very close to each other. We perform uniform smoothing along the local ridge orientation, and Gaussian smoothing normal to it. The kernel of the smoothing filter currently used is the normalized product of a 3 x 1 uniform-averaging kernel and a 1 x 5 Gaussian kernel of standard deviation 1.0. Possible orientations of the smoothing filter are discretized into 16 values. At each pixel, the appropriate filter is selected, according to the local orientation, and applied at the pixel's location.

Thinned ridges (valleys) are then obtained by finding local minima (maxima) normal to ridge directions. We deal with the problem that a few ridge (valley) pixels can be missing near some bifurcations by exploiting the fact that the missing points should have almost the same gray scale value in the smoothed image as that of the ridge (valley) points. In a small local area around each potential minutiae, we calculate the mean and the standard deviation of the gray levels, μ and σ. Let $v_{i,j}$ be the gray

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scale value of the point located at (i,j). If $v_{i,j} < \mu - k\sigma$, then we take this point as a connecting ridge point. On the other hand, if $v_{i,j} > \mu + k\sigma$, then we take this point as a connecting valley point. We choose a 4 x 4 local area, and $k = 1$.

c) Logical-Template-Based Minutiae Extraction: At this stage, ridge ends and bifurcations are extracted using logical templates. A template-matching approach has to consider three types of ridge variations: ridge width, ridge orientation, and angle between bifurcation ridges. Dependency on ridge width is eliminated by operating on the thinned ridge binary image, instead of the gray scale image. Furthermore, dependency on the angle between bifurcation ridges is eliminated by extracting bifurcations as end points in the valley image. Thus, only ridge orientation has to be considered. The straightforward approach is to apply the template at all potential locations and orientations. Such an exhaustive approach would be computationally expensive. In our system, the number of potential locations is significantly reduced by examining only a small subset of pixels that appear to belong to minutia. The number of possible orientations is also significantly reduced by utilizing the orientation image.

Let us denote a logical template by T. A logical template is rectangular in shape. It is composed of two rectangular sub-templates, T_r and T_g, which are concerned with detecting a ridge (valley) section, and the "gap" that follows it, respectively (see Figure 1). The lengths of T_r *and* T_g, *denoted by* l_r *and* l_g, respectively, correspond to minimum ridge length and minimum ridge gap length at an end minutiae. Thus, the dimensions of T are w x (l_r + l_g), where w is a width parameter that depends on factors such as data distortion and inter-ridge distance. In our experiments, we have $l_r = 6$, $l_g = 3$ and $w = 3$.

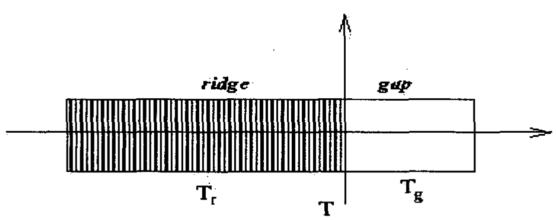

Figure 1. An illustration of a logical template.

The template logic can be explained as follows. Template T must return "true", iff both of its sub-templates return true as well. That is,

$$E = E_r \,\&\, E_g,$$

where E, E_r and E_g are logical expressions representing T, T_r and T_g, respectively. Ideally, E_r should return true, iff each column in the corresponding sub-template has at least one ridge (valley) pixel. Similarly, E_g should return true, iff there are no ridge (valley) pixels in the corresponding sub-template. That is,

$$E_r = (N(T_r) = l_r), \text{ and } E_g = (N(T_g) = 0),$$

where N (A) is a function that returns the number of non-zero columns in binary matrix A. In order to handle distortion and simplify the implementation, we use the following expression:

$$E = (w_r M(T_r) + w_g M(T_g)) \geq \Delta,$$

where M (A) is a function that returns the number of ones in binary matrix A, w_r and w_g are weights associated with the ridge and gap components of the logical expression and Δ is a threshold. The values of these parameters are determined in the following discussion.

The implementation of template matching can be described as follows. We dilate the ridge (valley) image in a direction normal to the local ridge (valley) direction, where the extent of dilation is adaptive to the local frequency. The local frequency is measured by the distance between ridges (valleys). Then, we apply 2-D templates along ridges. Note that the dilation approach is an alternative to adjusting the width of the logical template (parameter w) according to the local frequency. Since $l_r \neq l_g$, we assign $w_r = 1$ and $w_g = -2$. Accordingly, after template filtering the ideal value should be 18 for end points and 0 for ridge points. In order to deal with distortion, we empirically select threshold $\Delta = 12$ for ridge images, and $\Delta = 8$ for valley images. The use of different thresholds is needed since ridges and valleys tend to have different characteristics in our image set . In particular, the valleys tend to be wider than the ridges.

The actual minutiae extraction algorithm proceeds in two steps:

1. In order to improve efficiency, logical templates are applied to only a subset of ridge (valley) pixels that are likely to correspond to ridge (valley) ends. These points are selected by calculating the crossing number at each pixel, which is simply half the number of changes in pixel values when traversing the eight-neighborhood of a pixel [3]. Pixels with crossing number equal to one are selected as potential ridge (valley) ends.

2. The logical template is applied at each ridge (valley) pixel selected in the first step. The local ridge (valley) orientation is used to determine the orientation of the logical template. In particular, if θ is the local orientation, then the template is applied twice, at orientations θ and $\theta + \pi$.

d) Postprocessing: If the fingerprint image is of poor quality then we will have many false minutia. These extra minutia can be removed by postprocessing. For simplicity, the postprocessing in our experiments is that in a 4 x 4 local area centered at the potential minutiae, if $\mu_l + k_1\sigma_l < \mu_g + k_2\sigma_g$, then we ignore this minutiae, where μ_l, μ_g, σ_l, and σ_g are local mean, global mean, local standard deviation, and global standard deviation, respectively, and $k_1 = k_2 = 1$.

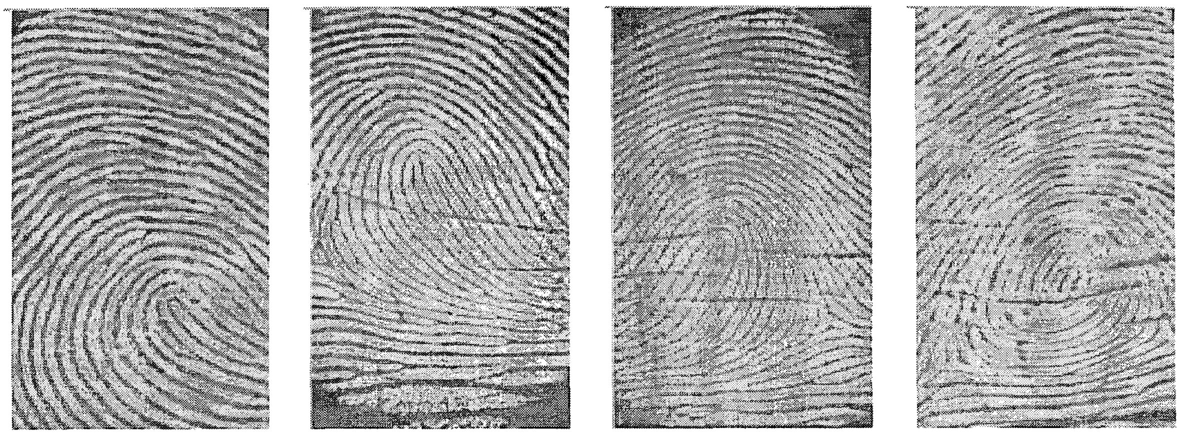

Image 1
Image quality: Very good

Image 2
Image quality: Good

Image 3
Image quality: Fair

Image 4
Image quality: Poor

Figure 2. Four fingerprint images of varying quality.

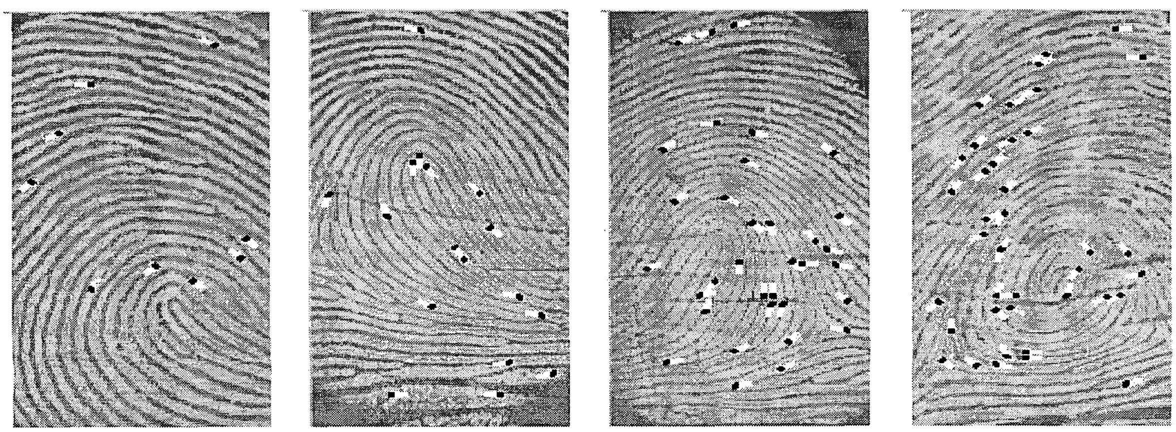

Figure 3. Logical templates placed on potential ridge-derived minutia (end points) in Figure 2.

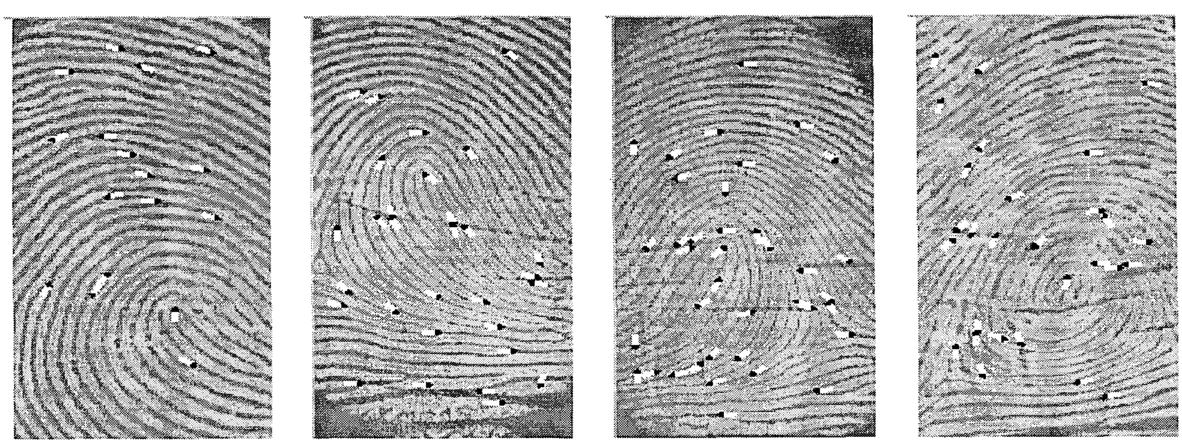

Figure 4. Logical templates placed on potential valley-derived minutia (bifurcations) in Figure 2.

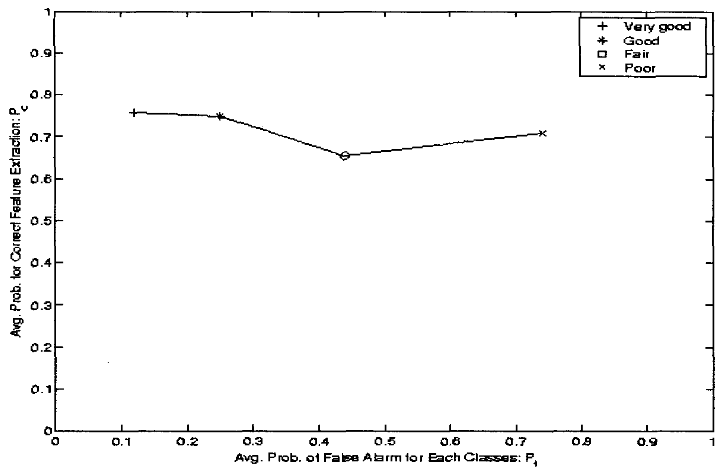

Figure 5. Performance of minutiae extraction (end points and bifurcations).

Table1. Typical experimental results for minutiae extraction on the images shown in Figure 2.

Image Quality and Image Number	Feature Type	# of Test Truth Features	Analysis of Computed Features			
			# of Features Found	# of Features Matched	# of Features Missed	# of Extra Features
Very good, Image 1	End points	10	8	8 (80.0%)	2 (20.0%)	0
	Bifurcations	15	13	12 (80.0%)	3 (20.0%)	1
Good, Image 2	End points	8	13	8 (100.0%)	0 (0.0%)	5
	Bifurcations	22	25	17 (77.3%)	5 (22.7%)	8
Fair, Image 3	End points	14	28	14 (100%)	0 (0.0%)	14
	Bifurcations	17	21	11 (64.7%)	6 (35.3%)	10
Poor, Image 4	End points	10	33	9 (90.0%)	1 (10.0%)	24
	Bifurcations	16	13	8 (50.0%)	8 (50.0%)	5

Table 2. Average experimental results based on 100 images for minutiae extraction.

Image Quality and # of Images in Each Class	Feature Type	Avg. # of Test Truth Features	Analysis of Computed Features			
			Avg. # of Features Found	Avg. # of Features Matched	Avg. # of Features Missed	Avg. # of Extra Features
Very good (25)	End points	11	11	9 (81.8%)	2 (18.2%)	2
	Bifurcations	22	18	16 (72.7%)	6 (27.3%)	2
Good (20)	End points	10	13	9 (90.0%)	1 (10.0%)	4
	Bifurcations	22	19	15 (68.2%)	7 (31.8%)	4
Fair (26)	End points	8	13	7 (87.5%)	1 (12.5%)	6
	Bifurcations	24	22	14 (58.3%)	10 (41.7%)	8
Poor (29)	End points	8	22	8 (100.0%)	0 (0.0%)	14
	Bifurcations	23	23	14 (60.9%)	9 (39.1%)	9
Avg. Results of 4 Classes of Image Quality	End points	9	15	8 (88.9%)	1 (11.1%)	7
	Bifurcations	23	21	15 (65.2%)	8 (34.8%)	6

3. Experimental Results

In this section, we present experimental results to demonstrate the performance of the proposed technique. The data set used in the experiments consists of 100 fingerprint images of pixel dimensions 248 x 120. They are obtained from a Sony fingerprint optical sensor (FIU-500-F01) of resolution 96 pixels per inch. We classify these images according to their quality into four classes:

- very good
- good
- fair
- poor

The quality of each image is determined visually based on the following criteria:

1) contrast between ridges and valleys,
2) ridge continuity and width, and
3) distance between ridges.

A sample of an image from each category is shown in Figure 2. Notice that the first two images, 1 and 2, are of considerably better quality than the last two images, 3 and 4. In particular, image 3 has many small cuts, while image 4 has broken ridges. In addition, notice the variations in the widths of the ridges and valleys in these images.

Processing proceeds as described in Section 2. The crossing number method for minutiae extraction results in a significant number of false minutia. These minutia are then filtered using the logical templates. These templates are applied to the ridge and valley images after being dilated according to the local measured frequency. Figures 3 and 4 show logical templates placed at the potential minutiae locations in the ridge and valley images, respectively. They are shown superimposed on the original images for examination.

Table 1 shows the experimental results of the images in Figure 1, and Table 2 shows the average results for the selected set of 100 fingerprint images. The test truth features are obtained by manual marking on the image. An extracted feature is considered to be matched if it lies within four pixels of a test truth feature. From the experimental results shown in Table 2, we observe the following:

1. The proposed approach is very effective in the extraction of end points. The average percentage of matched end points is 88.9%. However, it is less effective for extraction of bifurcations. The average percentage of matched bifurcations is 65.2%.

2. For both feature points, the rate of spurious features generated is strongly proportional to the image quality. This rate ranges from 12.1% for images of very good quality to 74.2% for images of poor quality.

Figure 5 shows the performance of feature extraction for the four image-quality classes. In this figure, the horizontal axis represents the probability of generating a spurious feature, while the vertical axis represents the probability of detecting a minutiae. As expected, we observe that false alarm tends to be proportional to the image quality. This suggests that considerable improvement in performance can by obtained by developing robust fingerprint enhancement techniques. This is a subject of our future research.

4. Conclusions

We have developed a novel technique for extraction of minutiae features from fingerprint images. The technique is based on adaptive logical templates for minutiae extraction in the presence of data distortion. Our future work will focus on refinement of the technique and use of these features for indexing and recognition of fingerprint images.

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