A New Approach for Fingerprint Minutiae Extraction

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Abstract. Minutiae extraction is a critical step in fingerprint identification, so it is important to find a proper approach to extract minutiae. In this paper, we propose a new method which extracts minutiae via principal curves. At first, we get a group of principal curves which reflect the structural features of the fingerprint; then we extract minutiae of fingerprint from these principal curves. From the result of experiment, we conclude that this new approach is feasible.

1 Introduction

Fingerprint minutiae include ridge bifurcation, ridge ending, short ridge and enclosure etc, these four sorts of fingerprint minutiae are shown in figure 1. Each individual has unique fingerprint, The uniqueness of a fingerprint is exclusive determined by the local ridge characteristics and their relationships [3]. Among various minutiae, ridge bifurcations and ridge endings are commonly used in fingerprint recognition. So far, there is much research for minutiae extractions, and most of algorithms for minutiae extraction are implemented based on thinning fingerprint images which compose of a set of pixels. However, when we look at the image of a fingerprint, we regard it as a collection of curves instead of a set of pixels. So, in this paper, we use principal curves to represent the skeletons of a fingerprint, and propose an approach to extract minutiae of fingerprints based on principal curves.

Principal curves were defined by Hastie and Stuetzle[1,2](thereafter HS) as "self consistent" smooth curves which pass through the "middle" of a d-dimensional probability distribution or data cloud. However, HS principal curves are not fit for represent fingerprint skeletons, so we choose the principal graph algorithm[2] to get skeletons.

Section 2 introduces the definition of principal curves and principal graph algorithm. Section 3 introduces our approach of minutiae extraction in details. Section 4 gives the experimental results. At the end of this paper, we give our conclusion in Section 5.

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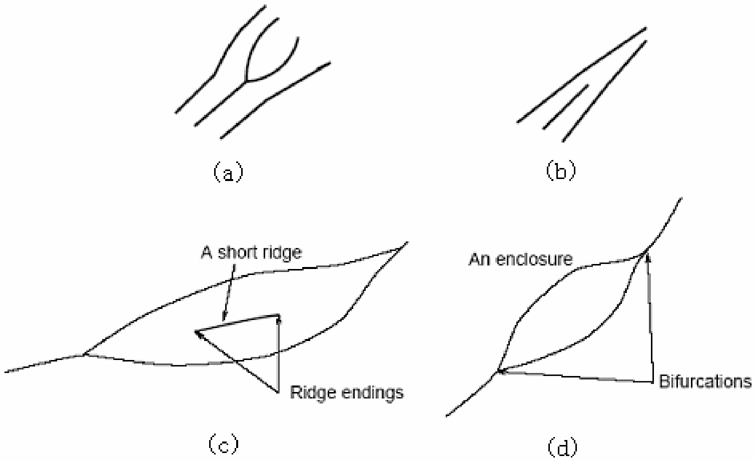

Fig. 1. Examples of minutiae. (a) ridge bifurcation (b) ridge ending (c) short ridge (d) enclosure

2 Definition of Principal Curves and Principal Graph Algorithm

In this section, we introduce the definition of principal curves [1, 2] and principal graph algorithm [2] proposed by Balazs Kegl.

2.1 Definition of Principal

Definition 1. Given a random vector $Y = (Y_1, Y_2, ..., Y_p)$ whose probability density is $g_y(y)$. If a smooth curve $f(s)$ which pass through the "middle" of the Y distribution satisfy:

$$f(s) = E(Y | s_f(y) = s) \tag{1}$$

$f(s)$ is a principal curve. $s_f(y)$ is the projection point of Y to $f(s)$, ie.

$$s_f(y) = \sup\{s : \|y - f(s)\| = \inf_{\tau} \|y - f(\tau)\|\} \tag{2}$$

Definition 2. The smooth curve $\mathrm{f}(t)$ is a principal curve if the following hold: 1) $\mathrm{f}(t)$ does not intersect itself, 2) $\mathrm{f}(t)$ has finite length inside any bounded subset of Rd 3) $\mathrm{f}(t)$ is self-consistent, i.e.

$$\mathrm{f}(t) = E[\mathrm{X} \mid t_{\mathrm{f}}(\mathrm{X}) = t] \tag{3}$$

By definition of the principal curve, we know that any point of the principal curve is the condition expectation of those points that project to this point, and it satisfies "self-consistent property". Theory foundation of principal curve is low-dimensional nonlinear manifold embedded in high-dimension space. Principal curves are nonlinear generalizations of principal components analysis. Figure 2 is a simple example. From Figure 2, we can find that the principal curve has two obvious advantages compared with first principal components: It can better keep information of data, on the other hand, it have less distance average variance, and it can better delineated out the outline of primitive information.

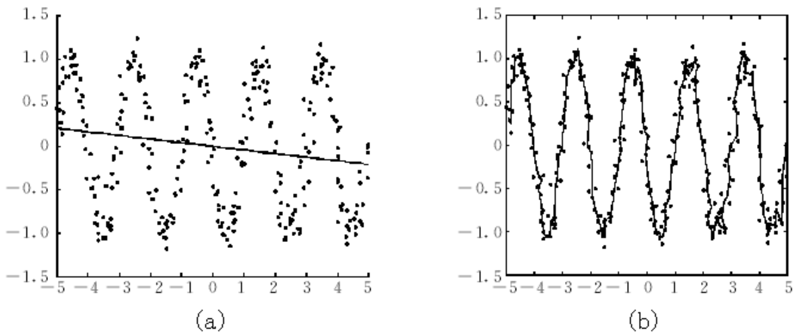

Fig. 2. (a) first principal components, (b) principal curve

2.2 Principal Graph Algorithm

In this paper, we adopt generalized principal graph algorithm which is proposed by Balazs Kegl to extract the skeleton of fingerprints. This algorithm is made up of the following several steps mainly:

The Initialization Step: A thinning algorithm is adopted to obtain the approximate skeletons of a graph. The skeleton is denoted by G_{vs}. G_{vs} consist of two sets V and S: $V = \{v_1, v_2, ..., v_n\} \subset R^d$ is a set of vertices, and $S = \{(v_{i1}, v_{j1}), ..., (v_{ik}, v_{jk})\} = \{s_{i1ji}, ..., s_{ikjk}\}$ is a set of edges.

Fitting-Smoothing Step: The objective of this step is adjusting smoothness of G_{vs} and making G_{vs} better fit for the graph. Given a dataset $X_n = \{x_1, x_2, ..., x_n\}$, it minimizes a penalized distance function $E(G) = \Delta(G) + \lambda P(G)$ to optimize G_{vs}. The first component $\Delta(G)$ is the excepted squared distance between points in X_n and G_{vs}. The second component $P(G)$ is a penalty on the average curvature of the graph. The smaller the value of $\Delta(G)$ is, the better the graph fits these data. The smaller the value of $P(G)$ is, the better smoothness of the graph is. In this step, projection step is done firstly. After projection step, the data points are partitioned into "nearest neighbor region" according to which segment or vertex they project. Then the vertex optimization step is performed to adjust the positions of vertexes and segments for finding a local minimum of $E(G)$.

The Restructuring Step: The step complements and perfects the fitting-smoothing step. It uses geometric properties of the skeleton graph to modify the configuration of vertices and edges. Goal of the step is to eliminate or rectify imperfections of the initial skeleton graph. For example removing short branches, removing short loops etc.

3 Approach for Minutiae Extraction Based on Principal Curves

In this section, we propose an approach to extract fingerprint minutiae based on principal curves which are generalized by principal graph algorithm. The steps as follow: At first, given a fingerprint image that has been enhanced by Gabor algorithm [3], all ridges are extracted from it. In this section, we choose two ridges as samples. Figure 3 shows a fingerprint image, and two ridge samples.

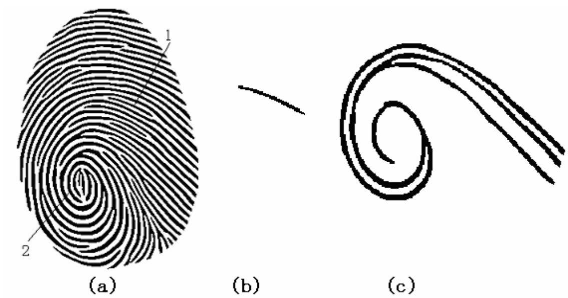

Fig. 3. (a)A enhanced fingerprint image. (b) A simple fingerprint ridge, (c) A complex fingerprint ridge

Then principal graph algorithm described in section 2.2 is used to get principal curves of ridges. We analyze a simple ridge shown in figure 3(b) firstly. Figure 4 is the principal curve of ridge shown in figure 3(b).

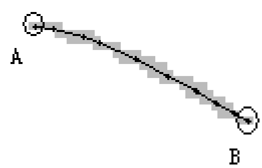

Fig. 4. A principal curved of a simple ridge

From figure 4, we find that the principal curve is fit to fingerprint ridge. The ridge consist of a single principal curve which is named $A^\frown B$ (Note: A and B are two endings of this principal curve). The data of the principal curve $A^\frown B$ are shown in table 1.

Table 1. The data of principal curve shown in figure 5

	Rectangular coordinate of Data points
	51.7608, 76.7328
	54.6401, 76.1603
	59.2785, 75.0582
$A^\frown B$	……
	79.3904, 65.3305
	82.2814, 63.6042
	84.2326, 62.4981

In fact, the principal curve $A^\frown B$ is a data set, and the first point and last point are two endings of principal curve. So our algorithm is just to analyze endings of principal curves and then extract the fingerprint minutiae. Before describe our algorithm, let's look at the principal curves of ridge shown in figure 3(c), figure 5 shows its principal curves.

Figure 5 shows that the ridge consist of 5 principal curves named $A^\frown B$, $B^\frown C$, $B^\frown D$, $C^\frown E$, $C^\frown F$, each principal curve is a dataset, and the first and the last point of dataset are two endings of each principal curve.
Basing on the analysis above, we propose an algorithm to extract minutiae from principal curves, it as follows:

1. **Searching Step:** Searching the first point and the last point of each principal curve: if a single point is only in one dataset, then it is looked as a ridge ending; else if a point is found in 3 dataset, then it is looked as a ridge bifurcation.
2. **Filtering Step:** Filtering the ridge endings and ridge bifurcation obtained in Searching Step, deleting the border points and pseudo minutiae.

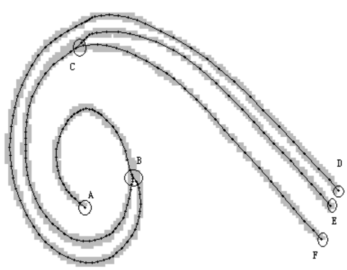

Fig. 5. Principal curved of a complex ridge

So we will obtain results via our algorithm that the point A and point B in figure 4 and point A in figure 5 is ridge endings, and that point B and point C in figure 5 is ridge bifurcation.

4 Experimental Results

In our experiment, we chose 320 pieces of fingerprint images with various qualities from FVC2002 fingerprint database (note: we use Gabor Filter to enhance the fingerprint image [3].). One result of our experiments is shown in figure 6. In this section, we define an accuracy rate as follows:

$$\mathrm{A} = 1 - \frac{p+l}{m-p+l} \tag{4}$$

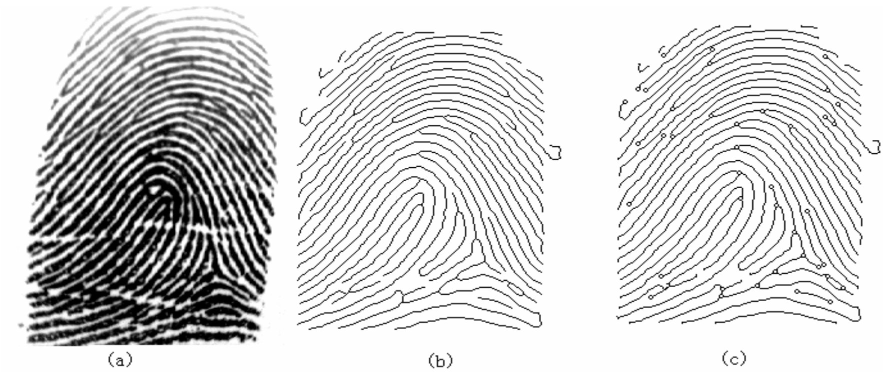

Fig. 6. (a) Original fingerprint; (b) Skeleton obtained by principal graph algorithm; (c) Minutiae obtained by algorithm described in section 3

In formula 4, p is the number of pseudo minutiae, l is the number of lost minutiae, and m is the number of minutiae obtained by our algorithm.

In our experiments, the average number of pseudo minutiae is 2.3, that of lost minutiae is 2.7, and that of obtained minutiae is 42.7. So the average accuracy rate is $\mathrm{A} = 1 - \frac{p+l}{m-p+l} = 88.4\%$, which is similar to the rate described in reference [6]. So we conclude that this algorithm is compatible with the requirement of fingerprint matching.

5 Conclusion

In this paper, principal curves are used to extract fingerprint minutiae. It is a new approach to minutiae extraction. From the results of the experiment, the accuracy of the approach suffices the requirement of fingerprint matching. For that using a collection of principal curves represent fingerprint skeletons, so we can get other information of minutiae more easily, such as minutiae's orientation and relationship which are used in fingerprint matching. From the result of experiments, we can conclude that minutiae extraction based on principal curves is feasible. Our future investigation is whether using minutiae which are extracted based on principal to fingerprint matching has more efficiency.

Acknowledgement

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