

Fingerprint minutiae extraction based on principal curves

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Abstract

It is important to extract minutiae of a fingerprint for the implementation of an auto fingerprint identification system. In this paper, the principal graph algorithm proposed by Kegl is used to obtain principal curves, which can be served as the skeletons of a fingerprint. Based on the obtained principal curves, a minutiae extraction algorithm is proposed to extract minutiae of the fingerprint. The experimental results indicate that principal curves obtained from the principal graph algorithm are smoother than the ones obtained from thinning algorithm, and the minutiae extracted by the proposed algorithm are more efficient.

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1. Introduction

Each human being has his/her unique fingerprints. The uniqueness of a fingerprint is determined by the characteristics and the relationships of local ridges, which are also called minutiae (Luo et al., 2000). Minutiae of a fingerprint include ridge bifurcations, ridge endings, short ridges and enclosures (Fig. 1). Among various minutiae, ridge bifurcations and ridge endings are commonly used in fingerprint recognition (Lin et al., 1998; Ratha et al., 1995). Up to now, there are many researches for minutiae extractions, and most of the algorithms are implemented by thinning a fingerprint image as a set of pixels (references are required here). However, while looking at the image of a fingerprint, we can regard it as a collection of curves instead of a set of pixels. For the tasks of fingerprint recognition and matching, we need to find a method that can get the skeleton of a fingerprint which includes a set of curves. After a series of study and research, we choose Kegl's algorithm (1999) of principal curve to do this work.

The definition of principle curves is provided by Hastie and Stuetzle as a set of self-consistent smooth curves which pass through the “middle” of a multi-dimensional probability distribution or data cloud (Hastie, 1984; Tibshirani, 1992; Zhang and Wang, 2003). So, by regarding a fingerprint as a data cloud, we can use a set of principal curves to present the skeleton of this fingerprint. Based on this result, we propose an algorithm to extract minutiae of a fingerprint from principal curves.

In the rest of the paper, Section 2 introduces the definition of principal curves and the principal graph algorithm. Section 3 presents our approach of minutiae extraction in details. Section 4 gives the experimental results. Finally, we present our conclusion in Section 5.

2. Definition of principal curves and principal graph algorithm

2.1. Definition of principal curves

Hastie and Stuetzle provided the definition of a principle curve, and emphasized its self-consistency property (property 3) as follows (Hastie, 1984; Zhang and Wang, 2003).

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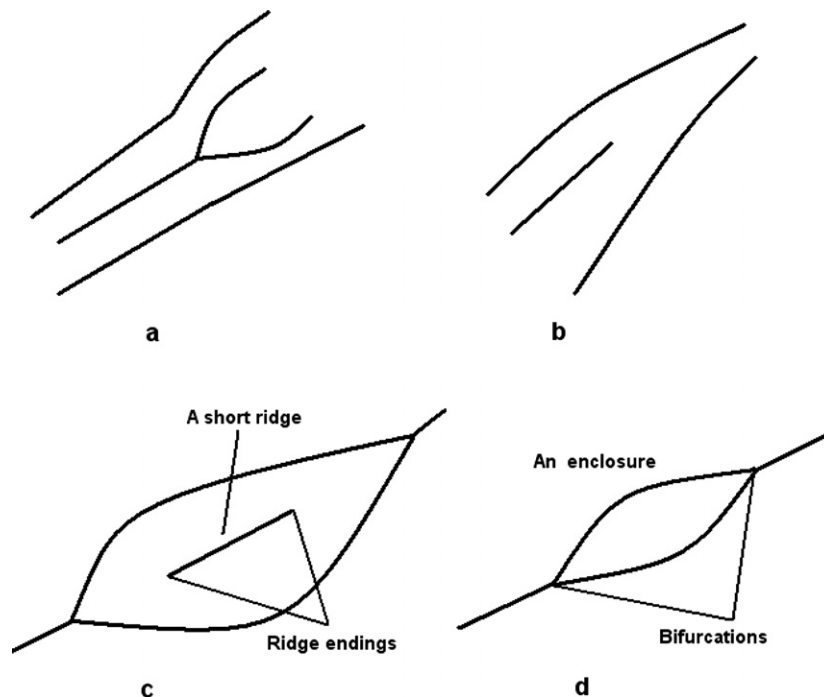


Fig. 1. Examples of minutiae. (a) A ridge bifurcation, (b) a ridge ending, (c) a short ridge, (d) an enclosure.

Definition 1: The smooth curve $f(t)$ is a principal curve if and only if:

- (1) $f(t)$ does not intersect itself,
- (2) $f(t)$ has finite length inside any bounded subset of R^d ,
- (3) $f(t)$ is self-consistent, i.e. $f(t) = E[X|t_\tau(X) = \tau]$.

The definition of a principal curve indicates that any point of the principal curve is the conditional expectation of those points that project to this point, and a principal curve satisfies the property of self-consistent. The theoretical foundation of a principal curve is a low-dimensional nonlinear manifold embedded in a high-dimensional space (Banfield and Raftery, 1992; Duchamp and Stuetzle, 1996). Principal curves are a nonlinear generalization of principal components analysis. Fig. 2 shows a first principal component line and a principal curve, and we can find that a principal curve has two obvious advantages compared with a first principal component: first, it can keep more information of data, and second, it can describe the outline of primitive information better. Since Hastie and Stuetzle's principal curves can not represent fingerprint skeletons directly, we choose the principal graph algorithm (Kegl, 1999) to get skeletons.

2.2. Principal graph algorithm

In this paper, we adopt a generalized principal graph algorithm proposed by Kegl (1999) to extract the skeleton of fingerprints. This algorithm contains the following main steps:

- (1) **Initialization:** A thinning algorithm is adopted to obtain the approximate skeletons of a graph. The skeleton is denoted by G_{vs} , which consists of two sets

V and S , where $V = \{v_1, v_2, \dots, v_n\} \subset R^d$ is a set of vertices, and $S = \{(v_{i1}, v_{j1}), \dots, (v_{ik}, v_{jk})\} = \{S_{i1j1}, \dots, S_{ikjk}\}$ is a set of edges.

- (2) **Fitting-smoothing:** The objective of this step is to adjust the smoothness of G_{vs} and to make it better fit the graph. Given a dataset $X_n = \{x_1, x_2, \dots, x_n\}$, this step minimizes a penalized distance function $E(G) = \Delta(G) + \lambda P(G)$ to optimize G_{vs} . The first component $\Delta(G)$ is the expected squared distance between points in X_n and G_{vs} , while the second component $P(G)$ is a penalty function 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 smoother the graph is. In this step, a projection step is done first. After the projection step, the data points are partitioned into "the nearest neighbor region" according to the segment or vertex they project. Finally the vertex optimization step is performed to adjust the positions of vertexes and segments for finding a local minimum of $E(G)$.
- (3) **Restructuring:** This step complements and perfects the fitting-smoothing step. It uses geometric properties of the skeleton graph to modify the configuration of the vertices and edges. The goal of the step is to eliminate or rectify imperfections of the initial skeleton graph such as removing short branches and short loops.

3. The approach for minutiae extraction based on principal curves

In this section, we describe the main steps of experiments by using a fingerprint ridge as a sample. A minutiae

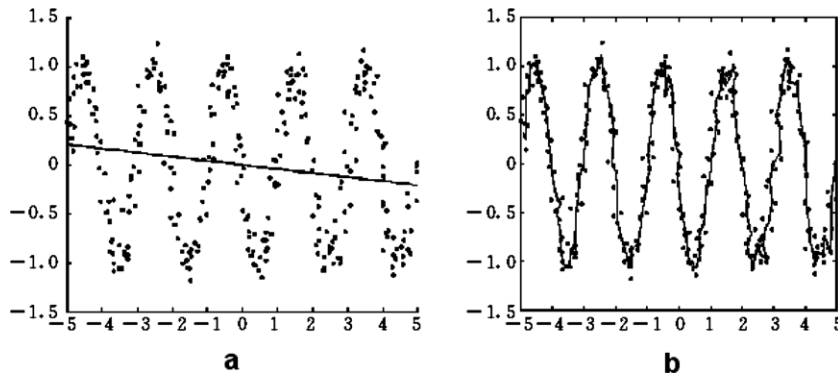


Fig. 2. (a) A first principal component line, (b) a principal curve.

extraction algorithm is proposed based on principal curves generalized by principal graph algorithm.

Suppose we have a fingerprint image enhanced by Gabor algorithm (Lin et al., 1998). Two ridges are chosen as samples (Fig. 3): one is a simple ridge, and the other is a complex ridge.

Then principal graph algorithm described in Section 2.2 is used to obtain principal curves of the ridges. We analyze a simple ridge shown in Fig. 3b first. Fig. 4 is the principal curve of the ridge shown in Fig. 3b. It shows that the principal curve fits the fingerprint ridge. The ridge consists of a single principal curve named AB (Note: Points A and B are two endings of this principal curve).

In fact, the principal curve AB is a data set, and the first point and last point are two endings of principal curve. So we can analyze endings of principal curves first and then extract the fingerprint minutiae. Before describing this, let's look at the principal curves of the ridge shown in Fig. 3c, Fig. 5 shows that the ridge consists of 5 principal curves named AB, BC, BD, CE, CF. Each principal curve is a dataset, with the first and last point of dataset being the two endings of each principal curve.

Based on the analysis above, we propose an algorithm to extract fingerprint minutiae from principal curves, which contains the following steps:

- (1) *Finding principal curve:* After enhancing the image of a fingerprint, we use the principal graph algorithm to



Fig. 4. A principal curve of a simple ridge.

get this fingerprint's skeleton which includes a set of principal curves.

- (2) *Extracting:* We check the first point and the last point of each principal curve: if a single point is only in one dataset, then it is regarded as an ending of a simple ridge. If a point is found in three datasets, then it is regarded as an ending of a ridge bifurcation.
- (3) *Filtering:* In this step, we filter the ridge endings and ridge bifurcations obtained in the extraction step. There are three kinds of pseudo minutiae:
 - (a) A pair of ridge endings caused by a broken fingerprint ridge. This kind of pseudo minutiae can be filtered by checking whether two ridge endings are close enough and the difference between their outcome directions approximate straight angle.
 - (b) A pair of ridge bifurcations caused by two mis-connected fingerprint ridge. This kind of pseudo minutiae can be filtered by checking whether two ridge bifurcations are close enough.

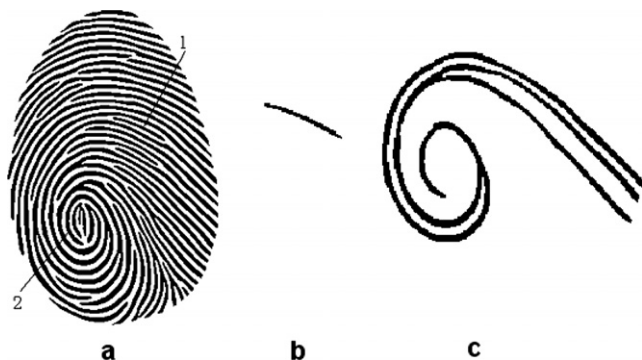


Fig. 3. (a) An enhanced fingerprint image, (b) a simple fingerprint ridge, (c) a complex fingerprint ridge.

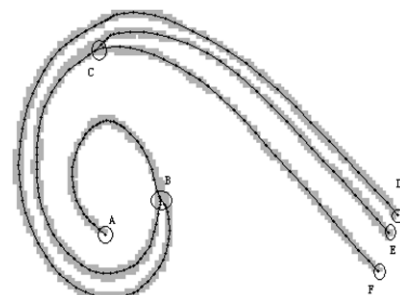


Fig. 5. Principal curves of a complex ridge.

- (c) The minutiae close to the border of fingerprint. This kind of pseudo minutiae can be filtered by checking whether the minutiae are close to the convex hull of the fingerprint.

By using this algorithm, we obtain the results such that in the first example, points A and B are endings of a simple ridge (Fig. 4), and in the second example, point A is an ending of a simple ridge and points B and C are the endings of ridge bifurcations (Fig. 5).

4. Experimental results

In our experiments, we chose 320 pieces of fingerprint images which are enhanced by the Gabor Filter (Lin et al., 1998) with various qualities from the FVC2002 fin-

gerprint database. One result of the experiments is shown in Fig. 6.

To compare the results of principle graph algorithm, we implemented the Zhang (Zhang et al, 1984) algorithms to fetch the skeletons of fingerprints. The results of these two algorithms are shown in Fig. 7. Set (a) illustrates four images of principle curves generated by the principle graph algorithms. Set (b) illustrates the skeletons of the corresponding images generated by Zhang algorithm. By a pairwise comparison, we can observe that the skeletons extracted by Kegl's principle graph algorithm can reflect the structures of fingerprints better than the ones generated by Zhang algorithm. The principal curves in Set (a) have smoother lines, higher accuracy, and less error-prone than the ones in Set (b) generated by the traditional thinning method.



Fig. 6. (a) Original fingerprint; (b) an enhanced image of fingerprints; (c) the skeleton of fingerprints composed by a set of principal curves and the minutiae.

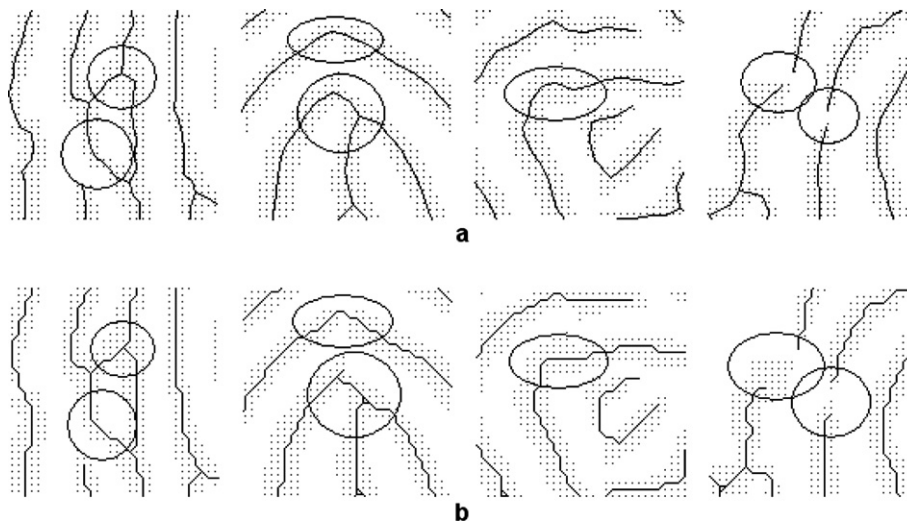


Fig. 7. The comparison with the skeletons extracted by the principal graph algorithm and the thinning algorithm. (a) The skeletons of fingerprints extracted by the principal graph algorithm, (b) the skeletons of fingerprints extracted by the thinning algorithm.

However, unfortunately, the performance of principal graph algorithm is worse than that of Zhang algorithm because we use a thinning algorithm to get an initial skeleton at first. Although the principal graph algorithm is slower than Zhang algorithm to get the skeleton of a fingerprint, it obtains more information such as the topology of a fingerprint, and thus we can use the information to extract the minutiae and match the fingerprints, and also it will increase the performance of minutiae extraction and fingerprints matching. In our experiment, we implement the algorithm proposed in this paper to extract the minutiae and compare it with the algorithm proposed by Yin et al. (2002).

As for the evaluation of minutiae extraction, we can use the accuracy rate (A) described below:

$$A = 1 - (p + l)/(m - p + l) \quad (1)$$

where p is the number of pseudo minutiae, l is the number of lost minutiae, and m is the number of minutiae obtained

Table 1
The partial results of minutiae extraction

	Minutiae	Pseudo minutiae	Lost minutiae
1	57	0	3
2	45	1	3
3	45	3	2
4	55	3	1
5	33	2	3
6	44	1	1
7	52	3	2
8	58	1	1
9	48	4	2
10	82	9	3
11	55	0	1
12	54	0	3
13	45	1	3
14	25	0	2
15	35	2	1
16	34	1	3
17	40	1	1
18	27	0	2
19	36	4	2
20	28	3	2
21	63	14	4
22	33	1	4
23	39	2	3
24	35	1	2
25	45	3	1

Table 2
The comparison with the performance of this paper and the one from Yin et al. (2002)

	Time for skeleton extraction (s)	Time for minutiae extraction (s)	Accuracy (%)
This paper	1.51	0.045	88.4
Yin et al. (2002)	–	0.18	87.0

by our algorithm. Table 1 is the part results of the experiment (the pseudo minutiae and lost minutiae are found manually).

The experimental results show that our average accuracy rate of minutiae is better than the rate reported by Yin et al. (2002).

In our experiments, the average number of pseudo minutiae, lost minutiae, and obtained minutiae are 2.3, 2.7, and 42.7. As a result, the average accuracy rate is 88.4%. Table 2 shows the comparison with the performance of the one by Yin et al. (2002).

5. Conclusion

In this paper, principal curves are used to extract fingerprint minutiae. It is a new approach for minutiae extraction. Our experiment results indicate that the accuracy of the approach is sufficient for the requirement of fingerprint recognition. By representing fingerprint skeletons with principle curves, we can get other information of minutiae more easily, such as minutiae's orientation and relationship which can be used in fingerprint recognition (Zhang and He, 2003). Based on this analysis, we can conclude that minutiae extraction using principal curves is feasible.

Moreover, our future research will use minutiae extracted from principal curves for fingerprint matching. We will compare this fingerprint matching approach with traditional approaches.

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