Plain Fingerprint Classification Based on a Core Stochastic Algorithm

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Abstract**:** We propose plain fingerprint classification based on a core stochastic algorithm that effectively uses a core stochastic model, acquiring more fingerprint minutiae and direction, in order to increase matching performance. The proposed core stochastic algorithm uses core presence/absence and contains a ridge direction and distribution map. Simulations show that the fingerprint classification accuracy is improved by more than 14%, on average, compared to other algorithms.

Keywords**:** Fingerprint core, Classification, Ridge direction, Stochastic model, Distribution map

1. Introduction

Fingerprint classification is a step that increases the efficiency of a *1*:*N* fingerprint recognition system and helps to reduce the matching time needed by such systems [1, 7-11]. A fingerprint recognition system captures a fingerprint and compares it with the information stored in a database to establish or authenticate the user's identity. If an identity is claimed, the system compares the query fingerprint only with the template corresponding to that identity stored in the database. This one-to-one matching process is called fingerprint verification. If no identity is claimed, the system needs to compare the query fingerprint with all templates stored in the database to establish the identity. This one-to-many matching process is called fingerprint identification. The extension of one-to-one matching of a verification system to one-to-many matching of an identification system increases the possibility of a false positive match. Compared to verification performance, both accuracy and speed can significantly deteriorate if a verification algorithm is naively extended to solve an identification problem. The performance deterioration could be very serious for large-scale identification systems beause performance is directly proportional to the number of fingerprints in the database [2]. This problem can be alleviated by reducing the search space of exact matching. Fingerprint classification, indexing, or retrieval techniques facilitate reduction of the search space. They can be viewed as a coarse-level pre-matching process before further exact matching in an identification system. Over the past few decades, people have put forward a lot of fingerprint classification algorithms, which are divided into four types [3]. In this paper, we propose an approach to designing a core detection and stochastic model using a directional characteristic of fingerprints for effective classification. We believe that this algorithm, based on core stochastic algorithms, can also achieve good results for fingerprint classification.

2. Fingerprint Recognition System

This section provides a basic introduction to fingerprint recognition systems and their main components, including a brief description of the most widely used techniques and algorithms. Fig. 1 shows the main modules of a fingerprint recognition system. Data capture (fingerprint sensing) is where the fingerprint of an individual is acquired by a fingerprint scanner to produce a raw digital representation.

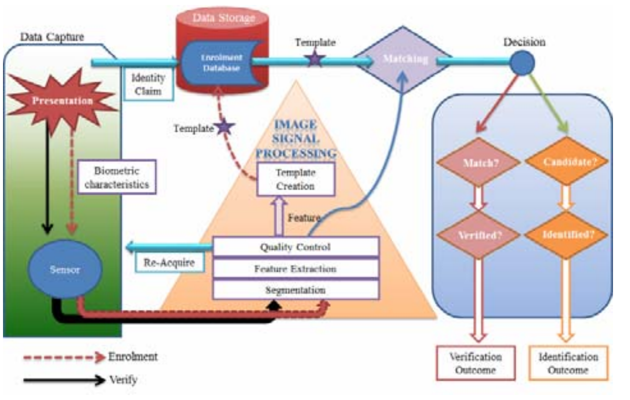

Fig. 1. Main modules of a fingerprint recognition system.

Next comes preprocessing, in which the input fingerprint is enhanced and adapted in order to simplify the task of feature extraction. Fingerprint feature extraction is where the fingerprint is further processed to generate discriminative properties, also called feature vectors. The final step, matching, is when the feature vector of the input fingerprint is compared against one or more existing templates. The templates of approved users for a biometric system, also called clients, are usually stored in a database. Clients can claim an identity, and their fingerprints can be checked against the stored fingerprints.

2.1 Fingerprint Data Capture Method

The acquisition of fingerprint images has been historically carried out by spreading the finger with ink and pressing it against a paper card. Currently, it is possible to acquire fingerprint images by pressing the finger against the plain surface of an electronic fingerprint sensor. This process is known as online acquisition. There are three families of electronic fingerprint sensor based on sensing technology [3].

- Solid-state or silicon sensors: These consist of an array of pixels, each pixel being a sensor itself. Users place the finger on the surface of the silicon, and four techniques are typically used to convert the ridge/valley information into an electrical signal: capacitive, thermal, electric field, and piezoelectric. Since solid-state sensors do not use optical components, their size is considerably smaller and they can easily be embedded. On the other hand, silicon sensors are expensive, so the sensing area of solid-state sensors is typically small.
- Optical device: The finger touches a glass prism and the prism is illuminated with diffused light. The light is reflected at the valleys and absorbed at the ridges. The reflected light is focused onto a CCD or CMOS sensor. Optical fingerprint sensors provide good image quality and a large sensing area, but they cannot be miniaturized because, as the distance between the prism and the image sensor is reduced, more optical distortion is introduced in the acquired image.

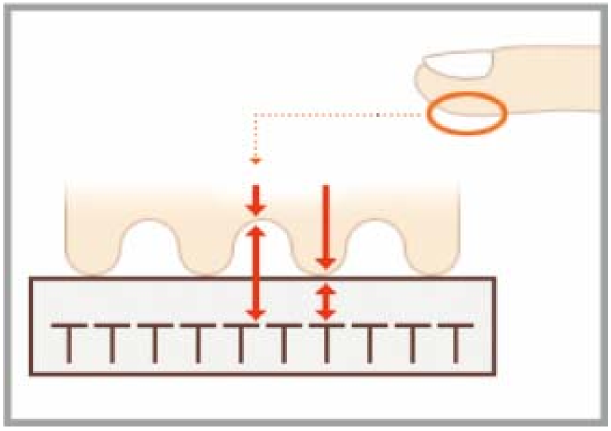

Fig. 2. Solid-state capture method.

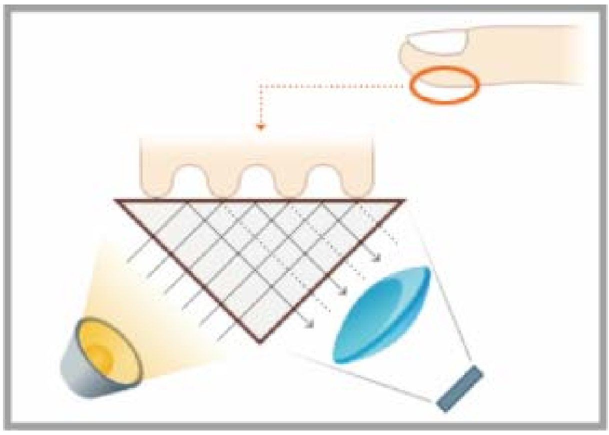

Fig. 3. Optical capture method.

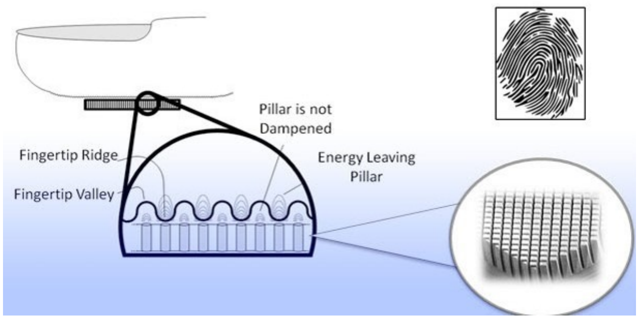

Fig. 4. Ultrasound capture method.

- Ultrasound device: Acoustic signals are sent, capturing the echo signals that are reflected at the fingerprint surface. Acoustic signals are able to pass through dirt and oil that may be present on the finger, thus giving good-quality images. On the other hand, ultrasound scanners are large and expensive, and take several seconds to acquire an image.

2.2 Fingerprint Feature Extraction

A fingerprint is composed of a pattern of interleaved ridges and valleys. The ridges are thinned and the resulting

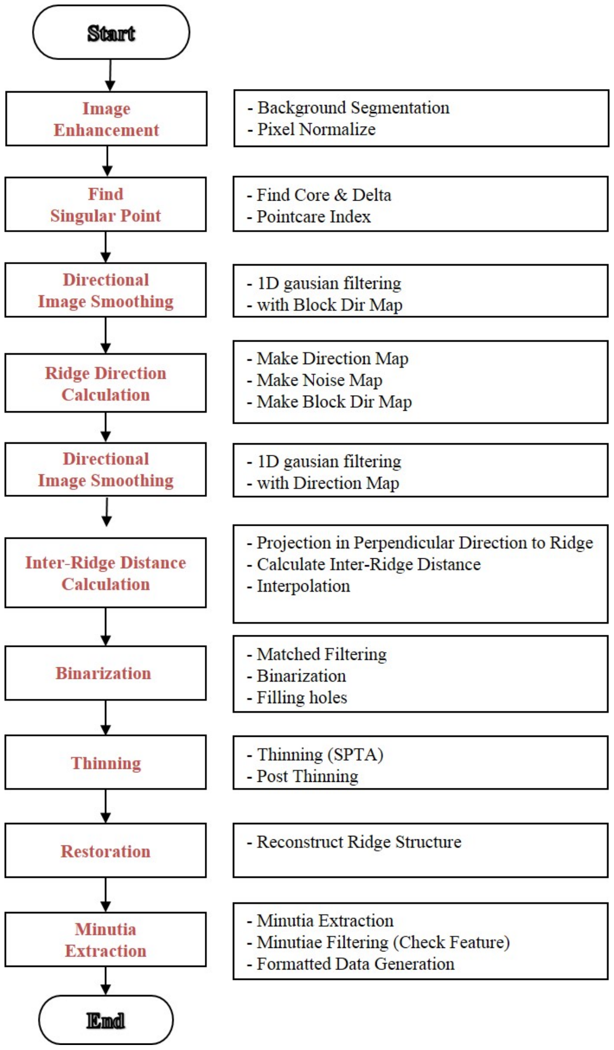

Fig. 5. Fingerprint feature extraction diagram.

skeleton image is enhanced using an adaptive morphological filter. The feature extraction stage applies a set of operations to the thinned and enhanced ridge image. The post-processing stage deletes noise from the feature points. The overall process can be divided into the following operations:

- Load the image
- Enhance the image
- Find singular points
- Apply first directional image smoothing
- Make ridge direction calculation
- Apply second directional image smoothing
- Calculate inter-ridge distance
- Invoke binarization
- Apply thinning
- Invoke restoration
- Apply minutia extraction

Images detailing the feature extraction process are shown in Fig. 6.

The final step is to save the details of the minutiae points (Fig. 5). A text file is generated to save the calculated minutiae points and the angles of the minutiae points. The crossing number concept is used for calculation of bifurcation and termination points in the fingerprint image. Then, the second step is to calculate the angle of the minutiae points corresponding to the neighboring pixels. The calculated minutiae points and bifurcation points are then saved in the ‘*.min’ file.

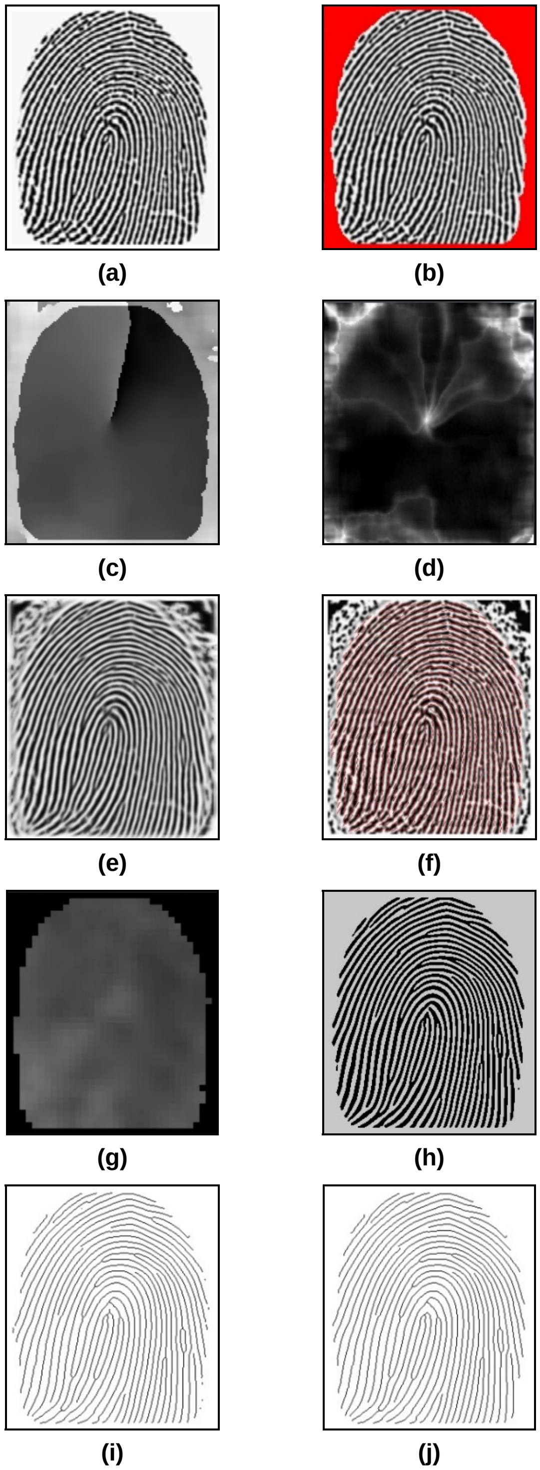

Fig. 6. Feature extraction steps: (a) enhancement, (b) segmentation, (c) direction, (d) noise, (e) smoothing, (f) block dir, (g) ridge width, (h) binarizing, (i) thinning, and (j) restoration.

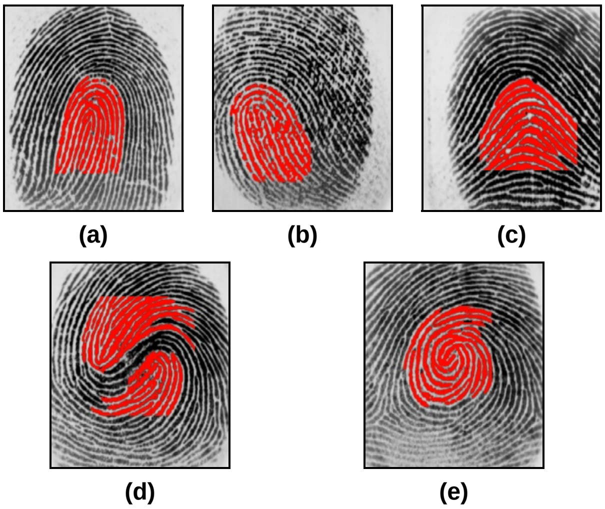

Fig. 7. Examples of fingerprints. (a) Left loop, (b) right loop, (c) arch, (d) double loop, and (e) whorl.

Table 1. Fingerprint patterns.

No	Pattern	(%)	Core
1	Loop	65	**Presence**
2	Whorl	30	**Presence**
3	Arch Pattern	5	Absence

3. Fingerprint Classification

Fingerprint classification images are very important in order to speed up the recognition process. In it, fingerprints are classified according to the shapes of minutiae ridges. It is an indexing algorithm for a large database. Using classification, fingerprint data are categorized into many types, such as patterns, minutiae points, pores and ridges, contours, etc. Populations around the world have different types of fingerprint patterns [4]. The fingerprint is divided into five categories: left loop, right loop, arch, double loop and whorl (Fig. 7). The arch is a type of ridge. The loop is a special property of the fingerprint image. A whorl pattern is one of the basic patterns in the human fingerprint in which at least one ridge tends to make a complete circuit. The results of a survey to judge which fingerprint pattern has maximum availability in the human population are shown in Table 1 [5].

4. Core Stochastic Algorithm

The proposed algorithm consists of three steps (Fig. 8). The first step is to compute the directional distribution map. One way to detect edges or variations within a ridge of an image is by using a gradient operator. The second step is core detection. If the characteristics of the directional angle range within 90°, it will be estimated as the core. The third step is to divide fingerprint classification according to the presence of the core. This step performs fingerprint classification according to the directional distribution in

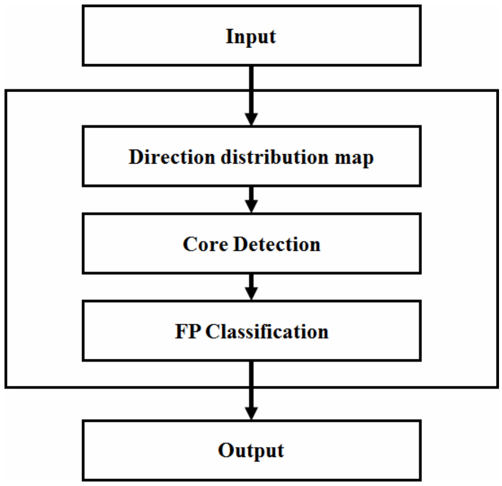

Fig. 8. Fingerprint feature extraction diagram.

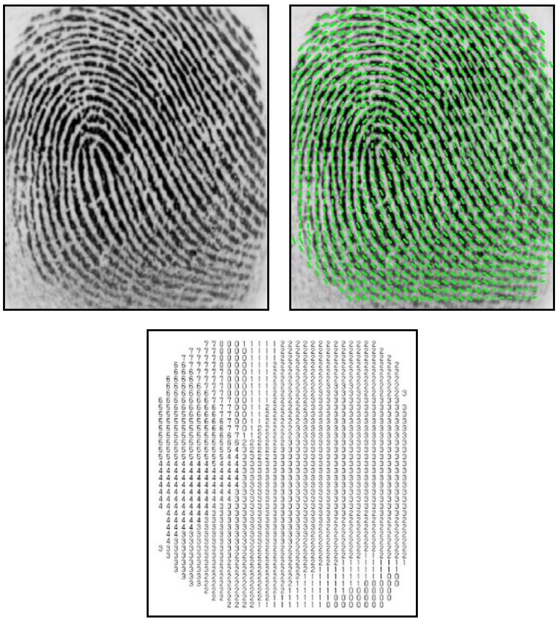

Fig. 9. Classification process result.

the divided classification type. To obtain a directional distribution analysis, use a stochastic model. Fig. 9 shows an extracted directional distribution map and fine core minutiae.

5. Experiments

This section focuses on evaluating the proposed algorithm. We start by describing the test data. Then, the experiment results of the proposed algorithm are presented for several real captured images. Finally, the effectiveness of the proposed algorithm is discussed through comparison with an existing algorithm [6].

The experiments were performed on an 32-bit Coretex-A5 core at 536 MHz, and the proposed algorithm was implemented using the GCC 4.6.3 development tool.

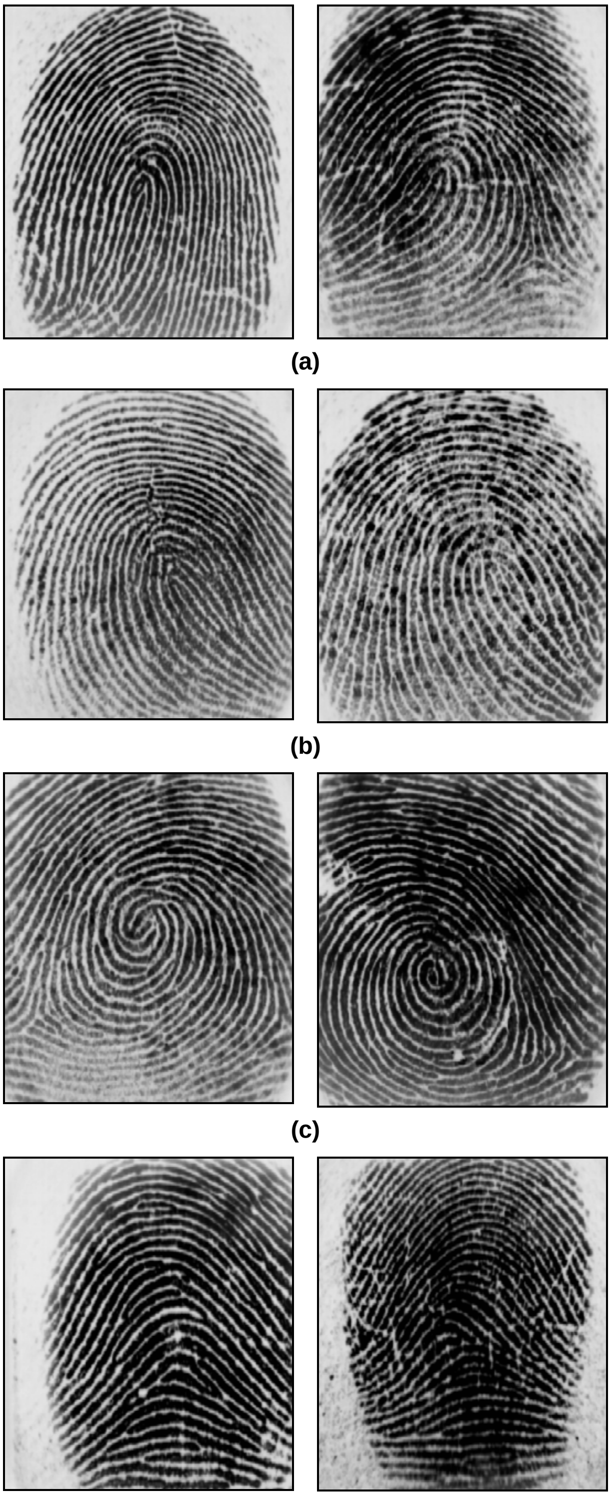

Fig. 10. Sample data. (a) Left loop, (b) right loop, (c) whorl, and (d) arch.

5.1. Test Data

In this work, the fingerprints used for testing the performance of the proposed algorithm came from a real captured database. The database contains 3,000 pairs of eight-bit grayscale fingerprint images with a size of 260 x 300. Some sample images used in the experiments are shown in Fig. 10.

Table 2. The comparison results.

Type	Total class fingerprint	**Poincare Algorithm**	The Proposed Algorithm
Left loop	1,472	1,030	1,266
Right loop	1,304	926	1,082
Arch	207	126	180
Whorl	17	12	14

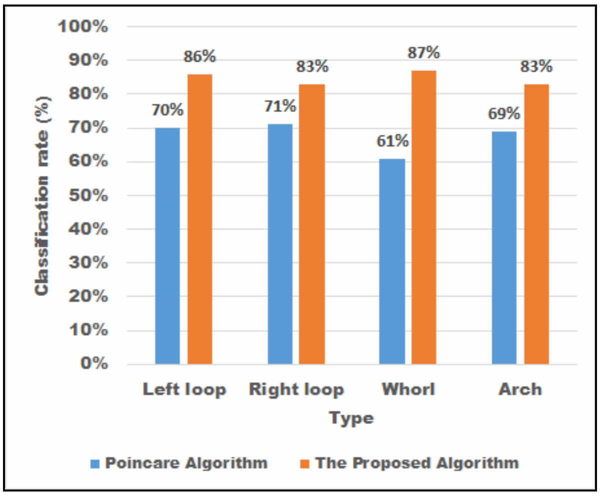

Fig. 11. Classification results of the test data.

5.2. Classification Results

Classification results from the proposed algorithm were compared with those from an existing algorithm. To provide a comparative study, we first compared the proposed algorithm with the Poincare algorithm as well as a multi-resolution–based algorithm [6].

Table 2 and Fig. 11 show the comparison results, which indicate high performance for all types. As can be seen in Table 2, left loop increased by 16%, right loop, whorl and arch increased by 12%, 26% and 14%, respectively.

6. Conclusion

Fingerprint classification is a step that increases the efficiency of a 1:N fingerprint recognition system, and helps to reduce the matching time needed by the fingerprint recognition system.

In this paper, we proposed a core stochastic algorithm that improves performance without upgrading the hardware.

The proposed algorithm was tested on natural fingerprint images. The results show that fingerprint classification accuracy improved by more than 14%, on average, compared to the Poincare algorithm, which proves that our algorithm offers excellent performance. In future work, we will need to improve fingerprint classification accuracy. In addition, we will research a fake-fingerprint–detection algorithm.

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