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Fingerprint Recognition Using a Reference Point and Pores

Kalyani Mali
Department of Computer Science & Engineering,
University of Kalyani, Kalyani, West Bengal, India
E-mail: kalyanimali1992@gmail.com

Samayita Bhattacharya
Department of Computer Science & Engineering,
University of Kalyani, Kalyani, West Bengal, India
E-mail: samayita.bhattacharya@gmail.com

***Abstract* – Biometrics is one of the biggest tendencies in human identification. The fingerprint is the most widely used biometric. However considering the automatic fingerprint recognition a completely solved problem is a common mistake. There are many different algorithms being used to get this accomplished. The global level structures consist of many ridges to form some specific shape like arch, loop, and whorl. Local level structures are called minutiae, which further classified as either endpoints or bifurcations. Either of which can be used to identify the fingerprint. The most popular and extensively used method is the minutiae-based method. In our method we used pores as the fingerprint feature.**

***Keywords* – AFRS, Fingerprint, Global Structure, Local Structure, Average Gradient, Core, Delta, Point Orientation, Singular Point, Directional Field, Ridge, Valley, Bifurcation, Ridge Ending, Minutiae, Pores.**

I. INTRODUCTION

Fingerprints are the graphical flow-like ridges present on human fingers. Finger ridge configurations do not change throughout the life of an individual except due to accidents such as bruises and cuts on the fingertips. This property makes fingerprints a very attractive biometric identifier. Fingerprint-based personal identification has been used for a very long time [1]. Owning to their distinctiveness, stability durability, and convenience, fingerprints are the most widely used biometric features.

The fingerprint is a duplicate of a fingertip epidermis when a person touches a smooth surface, the fingertip epidermis characteristic transferred to the surface. The pattern of the ridges and valleys on the human fingertips forms the fingerprint images.

Analyzing this pattern at different levels reveals different types of features that are, global feature and local feature. Global features shape a special pattern of ridge and valleys, called singularities or Singular Point (SP) and the important points are the core and the delta. The core defined as the most point on the inner most ridges and a delta defined as the centre point where three different directions flows meet. The SP provides important information for fingerprint classification, fingerprint matching and fingerprint alignment.

Local features so-called minutiae are an important feature for fingerprint matching.

Fingerprint patterns are full of ridges and valleys. The information of the ridge structures can be treated as three levels. At the coarse level, the number and the relative positions of singular points, including cores and deltas, are concerned for classification. At the fine level, the minutiae, a group of ridge endings and bifurcations, are used as the features for matching. Between the above two levels, the middle level also contains important information, including local ridge orientation (LRO) and local ridge frequency (LRF). Conventionally, only the structures of LROs are used to find the singular points for classification or to enhance ridge structures for minutiae extraction.

The first step in an identification system is often continuous classification of fingerprints. This reduces the partition of the database to be searched for matches. To facilitate high-performance classification, algorithms for accurate singular-point estimation are needed. Singular point detection is a critical process for both fingerprint matching and fingerprint classification. The process of singular points detection must be fast and robust; otherwise, the performance of the whole fingerprint recognition system would be influenced heavily.

In high level fingerprint classification algorithms, extracting the number and precise location of singular points (SP), namely core and delta points are of great importance. According to the number and location of these robust characteristics, fingerprints can be classified in to five main groups; arch, tented arch, right loop, left loop, and whorl.

Using high-level classification process can efficiently reduces the search area in large fingerprint databases and therefore speeds up the subsequent matching algorithm. There are four main approaches to allocate SPs [24].

1) Methods based on mathematical model representation of fingerprint, 2) Methods based on statistical approaches, 3) Methods based on different frequency transforms and 4) Methods based on fingerprint structures. Some approaches combine several types of the above mentioned methods and make a new combined system.

Singular points detection is the most challenging and important process in biometrics fingerprint verification and identification systems. Singular points are used for fingerprint classification, fingerprint matching and fingerprint alignment.

Nowadays, most automatic fingerprint identification systems (AFIS) are based on matching minutiae, which are local ridge characteristics in the fingerprint pattern.

The two most prominent minutiae types are ridge ending and ridge bifurcation. Based on the features that the matching algorithms use, fingerprint matching can be classified into image-based and graph-based matching.
Image-based matching [2] uses the entire gray scale fingerprint image as a template to match against input fingerprint images. Graph-based matching [5], [8] represents the minutiae in the form of graphs. The high

computational complexity of graph matching hinders its implementation. To reduce the computational complexity, matching the minutiae sets of template and input fingerprint images can be done with point pattern matching [3], [4], [9], [11], [12].

In order to implement a successful algorithm, it is necessary to understand the topology of a fingerprint. A fingerprint consists of many ridges and valleys that run next to each other, ridges are shown in black and valleys are shown in white. The ridges bend in such ways as to form both local and global structures; either of which can be used to identify the fingerprint. The global level structures consist of many ridges that form arches, loops, whirls and other more detailed classifications, as shown in Figure 1. Global features shape a special pattern of ridge and valleys. On the other hand, the local level structures, called minutiae, are further classified as either endpoints or bifurcations. Other than usual minutia there are sweat pores in the fingerprint which can also be used for fingerprint matching.

One of the most popular biometric traits, fingerprints are widely used in personal authentication, particularly with the availability of a variety of fingerprint acquisition devices and the advent of thousands of advanced fingerprint recognition algorithms. Such algorithms make use of distinctive fingerprint features that can usually be classified at three levels of detail [26], as shown in Fig. 5 and referred to as level 1, level 2, and level 3.

Level-1 features are the macro details of fingerprints, such as singular points and global ridge patterns, e.g., deltas and cores (indicated by red triangles in Fig. 5). They are not very distinctive and are thus mainly used for fingerprint classification rather than recognition.

The level-2 features (red rectangles) primarily refer to the Galton features or minutiae, namely, ridge endings and bifurcations. Level-2 features are the most distinctive and stable features, which are used in almost all automated fingerprint recognition systems (AFRSs) [25]–[27] and can reliably be extracted from low-resolution fingerprint images (~500 dpi). A resolution of 500 dpi is also the standard fingerprint resolution of the Federal Bureau of Investigation for AFRSs using minutiae [28].

Level-3 features (red circles) are often defined as the dimensional attributes of the ridges and include sweat pores, ridge contours, and ridge edge features, all of which provide quantitative data supporting more accurate and robust fingerprint recognition.

Among these features, pores have most extensively been studied [28]–[41] and are considered to be reliably available only at a resolution higher than 500 dpi.

Our procedure is based on pores, as well as on global level structure for finding a reference point by which alignment and matching of two templates is to be accomplished. This is a new approach.

II. Background

Most approaches to recognizing a fingerprint involve five basic stages:

(i) Acquisition, where the image is obtained from hardware or a file;
(ii) Pre-processing, which may include noise reduction, image enhancements and error correction;
(iii) Structural extraction, where global and local structures may be found;
(iv) Post-processing, where the structures are converted into a more useful format;
(v) And then matching, where fingerprints are compared against a database.

III. AFRS

Automatic fingerprint recognition systems (AFRS) have been nowadays widely used in personal identification applications such as access control. Roughly speaking, there are three types of fingerprint matching methods: minutia-based, correlation-based, and image-based. In minutia-based approaches, minutiae (i.e. endings and bifurcations of fingerprint ridges) are extracted and matched to measure the similarity between fingerprints. These minutia-based methods are now the most widely used ones. Different from the minutia-based approaches, both correlation-based and image-based methods compare fingerprints in a holistic way. The correlation-based methods spatially correlate two fingerprint images to compute the similarity between them, while the image-based methods first generate a feature vector from each fingerprint image and then compute their similarity based on the feature vectors. No matter what kind of fingerprint matchers are used, the fingerprint images usually have to be aligned when matching them. So another important aspect of fingerprint matching is the fingerprint alignment methods, though in our method we have not considered the alignment methods.

In order to further improve the accuracy of AFRS, people are now exploring more features in addition to minutiae on fingerprints.

The recently developed high resolution fingerprint scanners make it possible to reliably extract level-3 features such as pores. Pores have been used as useful supplementary features for a long time in forensic applications. Researchers have also studied the benefit of including pores in AFRS and validated the feasibility of pore based AFRS.

Using pores in AFRS has two advantages. First, pores are more difficult to be damaged or mimicked than usually taken minutiae i.e. ridge endings and bifurcations. Second, pores are abundant on fingerprints.

Even a small fingerprint fragment could have a number of pores (refer to Fig. 2). Therefore, pores are particularly useful in high resolution partial fingerprint recognition where the number of minutiae is very limited.

As it can be seen in a good quality fingerprint image, the friction ridges are dotted with small circular openings – the sweat pores. The perspiration is exuded from these.

IV. Approach to Extract Singular Point

In Fig.2, a fingerprint is depicted. The information carrying features in a fingerprint are the line structures, called ridges and valleys. In this figure, the ridges are black and the valleys are white. It is possible to identify two levels of detail in a fingerprint. The directional field (DF) describes the coarse structure, or basic shape, of a fingerprint. It is defined as the local orientation of the ridge valley structures.

The DF is, in principle, perpendicular to the gradients. However, the gradients are orientations at pixel scale, while the DF describes the orientation of the ridge-valley structures, which is a much coarser scale. Therefore, the DF can be derived from the gradients by performing some averaging operation on the gradients, involving pixels in some neighborhood [13].

Various methods used to estimate the DF from a fingerprint are known including matched-filter approaches [9], [14], [15], methods based on the high-frequency power in three dimensions [16], 2- dimensional spectral estimation methods [15], and micro patterns that can be considered binary gradients [10].

These approaches do not provide as much accuracy as gradient based methods, mainly because of the limited number of fixed possible orientations. This is especially important when using the DF for tasks like tracing flow lines. The gradient-based method was introduced in [7] and adopted by many researchers, see, e.g., [9], [17], [18], [20].

The elementary orientations in the image are given by the gradient vector $[Gx(x,y)\ Gy(x,y)]^T$, which is defined as:

$$\begin{bmatrix} Gx(x,y) \\ Gy(x,y) \end{bmatrix} = \text{sign}\,(Gx)\,\nabla I\,(x,y)$$

$$= \text{sign}\,(\partial I(x,y)/\partial x) \begin{bmatrix} \partial I(x,y)/\partial x \\ \partial I(x,y)/\partial y \end{bmatrix} \qquad (1)$$

Where I(x,y) represents the gray-scale image.

The first element of the gradient vector has been chosen to always be positive. The reason for this choice is that in the DF, which is perpendicular to the gradient, opposite directions indicate equivalent orientations.

Next phase is the extraction of the SPs, which are the points in a fingerprint where the DF is discontinuous.

V. Approach to Extract Pores

Pores, also known as sweat pores, are located on finger ridges. They are formed in the sixth month of gestation due to the sweat-gland ducts reaching the surface of the epidermis. Once the pores are formed, they are fixed on the ridges and there can be between 9 to 18 pores along a centimetre of ridge [25].

A pore can be visualized as open on one print, but as closed on the other print depending on pressure and whether it is exuding perspiration.

Pore detection, without a loss of generality, is a trivial task.

In our method we have checked a surrounding of each ridge pixel to check if it is surrounded by other ridge pixel or no, if it is not surrounded by other ridge pixel then it denotes a presence of pore. For each pore the central pixel is stored.

It is also needed to go through the *Alignment stage*, where transformations such as translation, rotation and scaling between an input and a template in the database are estimated and the input pores are aligned with the template pores according to the estimated parameters [4].

VI. Image Acquisition

The first stage of any vision system is the image acquisition stage. Image acquisition is hardware dependent.

A number of methods are used to acquire fingerprints. Among them, the inked impression method remains the most popular one. Inkless fingerprint scanners are also present eliminating the intermediate digitization process [6].

VII. Pre-processing

This is an essential part of fingerprint recognition. In this step the image is made ready for the actual matching. The input of this phase is the original fingerprint image and the final output of this step is the pore dataset of that image.

Our proposed algorithm for pre-processing is as followed:

- Noise reduction
- Image normalization [42]
- Selection of the interest region [42]
- Pore extraction.

VIII. Matching

Matching is a key operation in the current fingerprint identification system. One of the most important objectives of fingerprint systems is to achieve a high reliability in comparing the input pattern with respect to the database pattern. Reliably matching fingerprint images is an extremely difficult problem, mainly due to the large variability in different impressions of the same finger (i.e., large intra-class variations).

The main factors responsible for the intra-class variations are: displacement, rotation, partial overlap, non-linear distortion, variable pressure, changing skin condition, noise, and feature extraction errors.

So fingerprints from the same finger may sometimes look quite different whereas fingerprints from different fingers may appear quite similar.

The method employed in the research was both SP and pore based matching. A pore matching essentially consists of finding the alignment between the template and the input pore sets that result in the maximum number of pore pairings. In pore based matching the similarity between the input and stored template are computed.

IX. Future Scope

In this paper, pore extraction based fingerprint detection was applied with gradient detection as a step, to find the reference point.

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The singular point detection method can be applied as a step to cluster the fingerprint images into five major groups, and then pore extraction based method can be applied on the clusters to achieve a hierarchical fingerprint detection algorithm. We are trying to incorporate this approach in future.

We are also investigating different soft computing approaches for calculating the reference point, as well as pores. By introducing soft computing tools we can add intelligence to the recognition system, so that the system can tell the possibility of the particular image to be on a particular database.

A more effective fingerprint recognition system might be implemented using singular points, pores and minutia.

X. Discussion and Conclusion

There have been many algorithms developed for extraction of both local and global structures. Most algorithms found in the literature are somewhat difficult to implement and use a rather heuristic approach.

The reliability of any automatic fingerprint recognition system strongly relies on the precision obtained in the extraction process. Extraction of appropriate features is one of the most important tasks for a recognition system.

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AUTHOR'S PROFILE

Dr. Kalyani Mali
received B.Tech. and M.Tech. Degree in 1987 and 1989 from University of Calcutta, India, and Ph.D. degree in Computer Science and Engineering from Jadavpur University, Kolkata, India in 2005. She joined the faculty of Department of Computer Science and Engineering, University of Kalyani in 1992. She currently holds the rank of associate professor. Her current research interests include pattern recognition, image processing, data mining and soft computing.

Samayita Bhattacharya
received her B.Tech. and M.Tech. degree in Information Technology from West Bengal University of Technology and Jadavpur University in 2006 and 2008. She is currently a Ph.D. Student in the Department of Computer Science and Engineering, University of Kalyani, India. Her current research interests include image processing, biometrics, soft computing and pattern recognition.

Fig.1. Fingerprint Patterns

Fig.2. Fingerprint image showing Minutiae

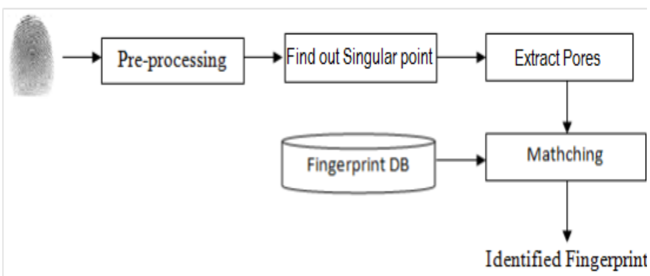

Fig.3. Stages of the fingerprint recognition process

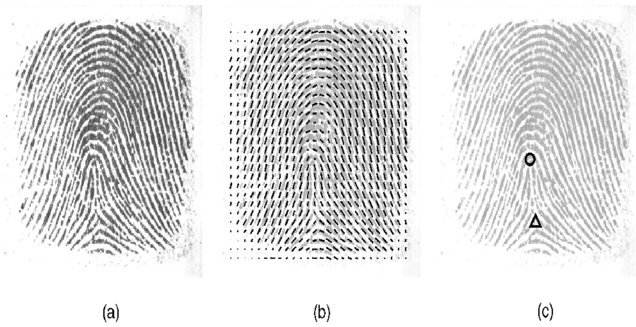

Fig.4. Examples of a fingerprint, its directional field and its singular points: (a) fingerprint, (b) directional field, and (c) singular points

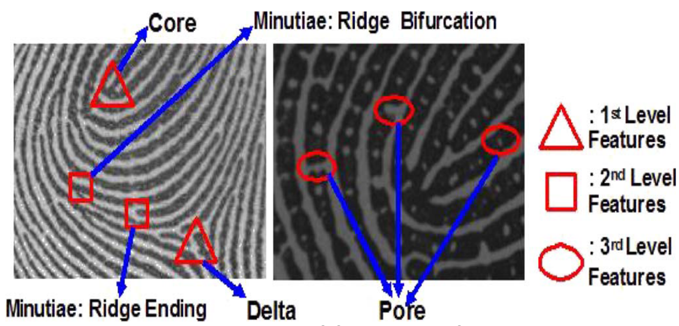

Fig.5. Three levels of fingerprint features

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(a)

(b)

(c)

Fig.6. Result of pre-processing steps. (a) original image, (b) image after noise reduction and normalization, (c) region of interest