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ANALYSIS OF BIOMATRICS USING MINUTIAE AND TEXTURE FEATURES

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ABSTRACT

Fingerprint is a reliable biometric which is used for personal verification. Current fingerprint verification techniques can be broadly classified as Minutiae-based, ridge feature-based, correlation-based and gradient-based. Biometrics recognition has been one of the standout research areas in the past decades as the demand for security systems increases, and fingerprint recognition remains as a popular choice due to the ease of acquiring such data and fingerprint is universally accepted as a feature that is unique to all individuals. One of the limitations of existing fingerprint ecognition techniques is that these systems tend to fall short when the available fingerprint is of low quality. This work describes a simple hybrid method that improves the performance of fingerprint recognition technique by fusing minutiae-based and image-based techniques, extracting features from both techniques to compensate the limitations of each of them. Results show that the proposed hybrid method is capable of achieving better recognition rate. Further analyses indicate that the percentage of similarity score and the Euclidean distance computation are both improved, in general. Minutiaebased matching algorithms, which consider ridge activity only in the vicinity of minutiae points, are not likely to perform well on these images due to the insufficient number of corresponding points in the input and template images. We present a hybrid matching algorithm that uses both minutiae (point) information and texture (region) information for matching the fingerprints.

KEYWORDS: Finger print, Minutiate, hybride matching.

INTRODUCTION

The fingerprint matching system rely on the distribution of minutiae on the fingertip to represent and match fingerprints. However, the solid-state fingerprint sensors provide a small contact area for the fingertip and, therefore, sense only a limited portion of the fingerprint. Thus multiple impressions of the same fingerprint may have only a small region of overlap. Minutiae based matching algorithms, which consider ridge activity only in the vicinity of minutiae points, are not likely to perform well on these images due to the insufficient number of corresponding points in the input and template images. Hence we used a hybrid matching algorithm that uses both minutiae (point) information and texture (region) information for matching the fingerprints.

PROBLEM STATEMENT

Fingerprint matching techniques can be broadly classified as being minutiae- or correlation-based. Minutiae-based techniques attempt to align two sets of minutiae points and determine the total number of matched minutiae [10,11,8]. Correlation based techniques, on the other hand, compare the global pattern of ridges and furrows to see if the ridges in the two fingerprints align [12,13]. The performance of minutiae-based techniques rely on the accurate detection of minutiae points and the use of sophisticated matching techniques to compare two minutiae fields which undergo non-rigid transformations. The performance of correlation-based techniques is affected by non-linear distortions and noise present in the image. In general, it has been observed that minutiae-based techniques perform better than correlation-based ones.

The pixel intensities in each sector are normalized to a constant mean and variance, and filtered using a bank of eight Gabor filters to produce a set of eight filtered images. Gray scale variance within a sector quantifies the underlying ridge structures and is used as a feature. The feature vector (640 values in length) is the collection of all the features, computed from all the 80 sectors, in every filtered image. The FingerCode captures the local information, and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The matching stage simply computes the Euclidean distance between the two corresponding FingerCodes. This technique, however, suffers from the following shortcomings:

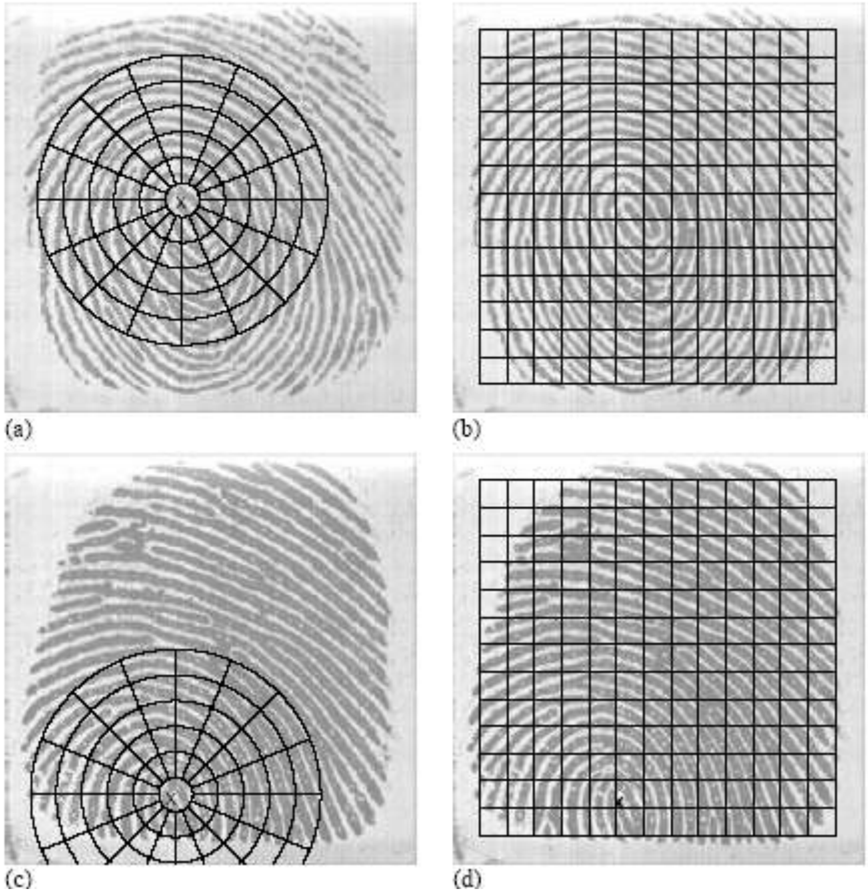

Figure 1: : Tessellating the "fingerprint image" using a circular and a square grid. The square tessellation, unlike the circular one, is not abetted by the location of the core point in the image: (a) circular tessellation about a core point; (b) square tessellation over the entire image; (c) circular tessellation about a core detected close to the boundary of the image; and (d) square tessellation over image in which the core has been detected close to the boundary of the image. The images were acquired using the Veridical sensor.

(1) The frame of reference is based on a global singular point (i.e., the core point). Detection of the core point is non-trivial; furthermore, the core point may not even be present in small-sized images obtained using solid-state sensors.
(2) The alignment is based on a single reference point and is, therefore, not very robust with respect to errors in the location of the reference point.

(3) The tessellation does not cover the entire image. Furthermore, if the core were to be detected close to the boundary of the image, the tessellation will include an extremely small portion of the image (Fig. 1.0(c)).

The technique proposed here has the following advantages:
(1) Unlike in Ref. [9], the filtering is done on the enhanced images rather than the raw input images. The enhanced images have lower noise content than the raw images.

(2) Instead of using circular tessellation, a square tessellation is used (Fig. 1.(b)). The tessellation includes the entire image, and all the tessellated cells are of the same size. Moreover, the tessellation is not based on detecting any landmark points.

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(3) The fingerprint images are aligned using the overall minutiae information; this is more robust than using only the core point for aligning image pairs.

FINGERPRINT SENSORS

The fingerprint images may be acquired either by an offline or an online process. The fingerprint images acquired by the offline process are known as the "inked" fingerprints while the images acquired by the online process are known as "live-scan" fingerprints. Inked fingerprints are of three types: (*i*) rolled, (*ii*) dab, and (*ii*) latent. In the rolled method of fingerprint acquisition, ink is applied to the finger and then rolled on a paper from one side of the nail to the other to form an impression. This paper is then scanned at 500 *dpi* resolutions by a standard grayscale scanner. The rolled fingerprints have a larger ridge and furrow area due to the rolling process but have larger deformations due to the inherent nature of the rolling process. In the dab method of fingerprint acquisition, ink is applied to the finger and then pressed onto a paper without rolling. The paper is then scanned into a digital image. Typically, dab inked fingerprints have less nonlinear deformation but smaller area than the rolled inked fingerprints.

Latent fingerprints are formed when the fingers leave a thin layer of sweat and grease on the surfaces that they touch due to the presence of sweat pores in our fingertips. Forensic scientists dye this impression, which is typically found at the scene of a crime with color, and then scan the fingerprint. In this thesis, we have concentrated only on civil applications of fingerprints and therefore, have not used the latent fingerprints. A live-scan fingerprint is obtained directly from the finger without the intermediate use of paper (at a resolution of 500 *dpi*). Typically, live-scan sensors capture a series of dab fingerprints when a finger is pressed on the sensor surface. For rolled live-scan fingerprints, the user rolls her/his finger from one end of the nail to the other on the sensor surface and the sensor captures a number of dab fingerprint images. The rolled fingerprint image is then constructed by mosaicking the multiple dab images captured during the rolling process. The commercially available live-scan sensors are based on several different technologies. The optical fingerprint sensor from Digital Biometrics Inc. (model FC21RS1) is based on the "optical total internal reflection" technology. The Thompson-CFS chip-based sensor works on thermal sensing of temperature difference across the ridges and valleys. The Veridicom and the Siemens sensors are based on differential capacitance. The pressure based and ultrasonic-based fingerprint sensors are available in the market, but they are not very widely used yet.

A number of commercial systems exist that use fingerprints captured by different methods. For example, FBI captures fingerprints of known criminals using the inked rolled method and stores the digitized fingerprint images in its database. A suspect's latent fingerprint found at a scene of crime is then matched to the rolled inked fingerprints in the database. As another example, MasterCard instructs the new credit card applicants to make an inked rolled impression of their finger on a paper and mail the paper to them. The inked rolled fingerprint is then scanned and stored in the user's credit card. The user is then verified at the time of credit card transactions using a dab live-scan fingerprint image obtained with the live-scan fingerprint scanner attached to the ATM.

An additional point worth mentioning in this section is that the FBI has prescribed a standard resolution of 500!*dpi* for fingerprint images. A large number of live fingerprint sensors available in the market today operate at this resolution. National Institute of Standards and Technology (NIST) provides a number of fingerprint databases to the research community for benchmark purposes. A number of these databases contain inked rolled fingerprints (e.g., NIST-4, NIST-9, etc). These databases contain fingerprint images scanned at 500 *dpi* from the paper copy of the rolled impressions as well as captured by 500 *dpi* live scanners. A few sensors that image the fingerprints at a lower resolution are also available in the market. However, since 500 *dpi* resolution is the standard, we use fingerprint images scanned only at this resolution in this thesis.

Figure 2.(a) shows a fingerprint image captured using the inked method. The NIST 9 database, CD. No. 1, contains 900 fingerprint images captured by this method. Figures 2.3(b) and (c) show fingerprint images captured by the optical live-scan sensor manufactured by Digital Biometrics, Inc. The inked method captures the largest fingerprint area. The chip-based sensors capture only a part of the whole fingerprint due to their small size. Two images of the same finger may capture different parts of the fingerprint. Due to this relatively small overlap between different images of the same finger captured with the small sensors, the fingerprint matching problem is challenging. However, due to their small size, the solid-state sensors can be easily embedded into laptops, cellular phones, mouse and firearms.

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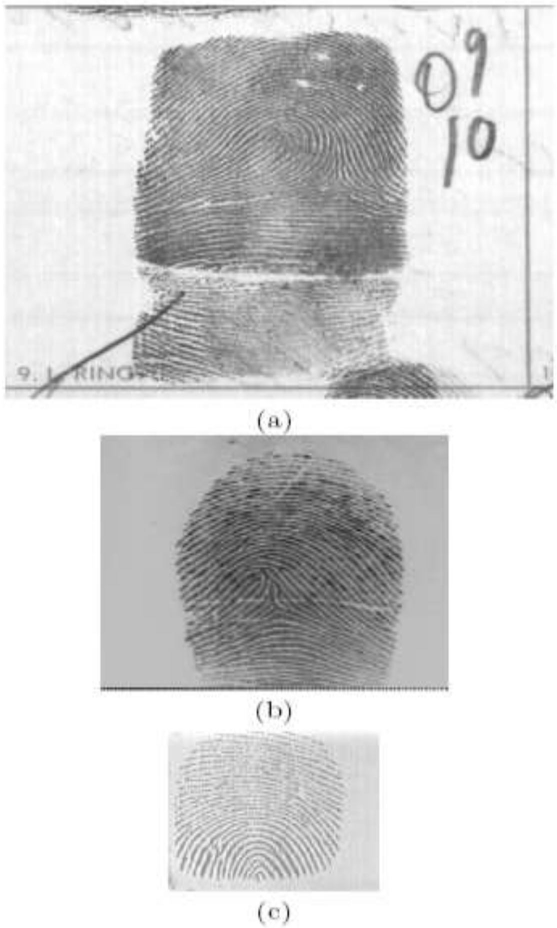

Figure 2: Fingerprint image captured using (a) inked method (b) Digital Biometrics optical sensor (c) Veridicom solid-state sensor

MINUTIAE BASED FINGERPRINT MATCHING TECHNIQUE

Most automatic systems for fingerprint comparison are based on minutiae matching. Minutiae characteristics are local discontinues in the fingerprint pattern which represent terminations and bifurcations. A ridge termination is defined as the point where a ridge ends abruptly. A ridge bifurcation is defined as the point where a ridge forks or diverges into branch ridges. Different types of minutiae are:

- Bifurcation
- Ridge Ending
- Enclosure
- Ridge Dot

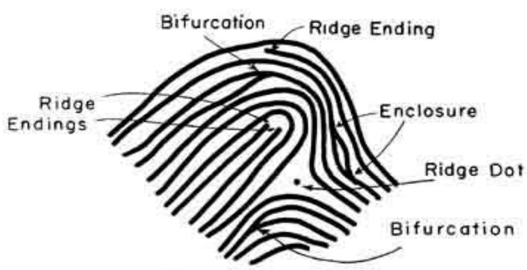

Figure 3: Minutiae

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Reliable automatic extraction of minutiae is a critical step in fingerprint classification. The ridge structures in fingerprint images are not always well defined, and therefore, an enhancement algorithm, which can improve the clarity of the ridge structures, is necessary. The process of extraction of minutiae and minutiae matching is done in the remainder of this section.

Minutiae Detection

The proposed method can only be performed on thinned images. It is known as crossing number or connectivity number. The technique uses a sample window, 3 pixels by 3 pixels wide to detect key features such as endpoints and bifurcation.

The formula for the detection of key points is:

$$CN = 0.5 \sum_{I=1}^{8} |P_i - P_{I+1}| \qquad \text{Where } P_1 = P_9$$

This is applied to the matrix:

P_4	P_3	P_2
P_5	P	P_1
P_6	P_7	P_8

CN	Characteristic
0	Isolated Point
1	End Point
2	Continuing Point
3	Bifurcation Point
4	Crossing Point

Table 1. Minutiae and the corresponding crossing number

Feature Extraction

A feature extractor finds the ridge endings and ridge bifurcations from the input fingerprint images. If ridges can be perfectly located in an input fingerprint image, then minutiae extraction is just a trivial task of extracting singular points in a thinned ridge map. However, in practice, it is not always possible to obtain a perfect ridge map. The performance of currently available minutiae extraction algorithms depends heavily on the quality of the input fingerprint images. Due to number of factors (aberrant formations of epidermal ridges of fingerprints, postnatal marks, occupational marks, problems with acquisition devices, *etc.*), fingerprint images may not always have well-defined ridge structures. A reliable minutiae extraction algorithm is critical to the performance of an automatic identity authentication system using fingerprints. The overall flowchart of a typical algorithms depicted in Figure 4.

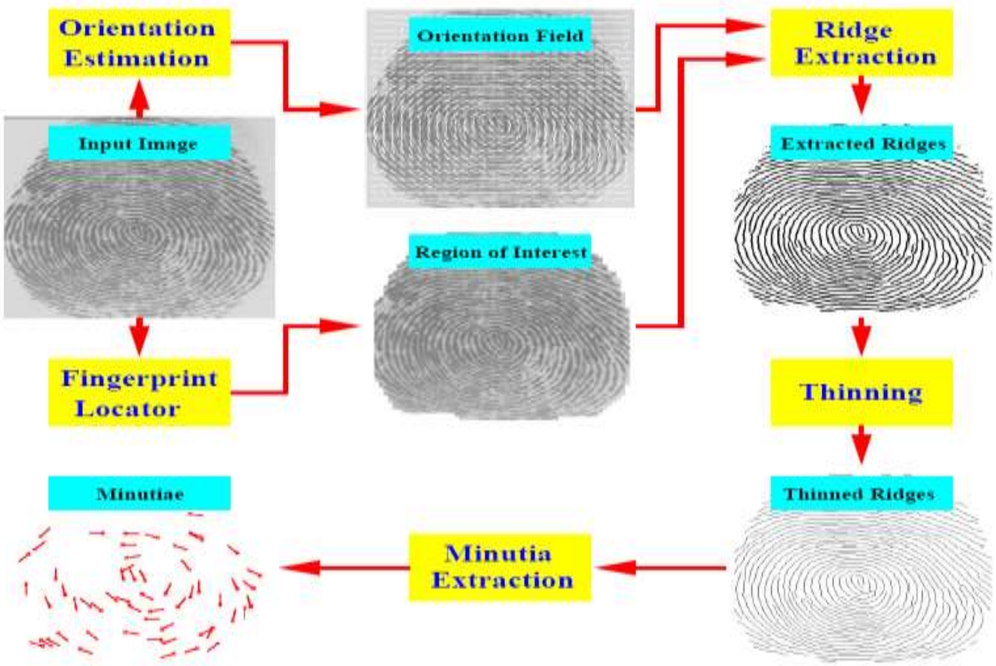

Figure 4: Flowchart of the minutiae extraction algorithm.

CONCLUSION AND FUTURE SCOPE

In this thesis, a fingerprint representation technique that uses ridge feature maps has been presented. Further, a hybrid fingerprint matching technique that combines minutiae information with the ridge feature map has been described. Experiments indicate that the hybrid technique performs much better than a purely minutiae-based matching scheme. Minutiae information is being used to align the query and the template images, before computing the ridge feature map of the query image. The following techniques are also being studied:
(1) New matching methods for comparing the ridge feature maps of two images.
(2) Development of fusion architectures to improve performance of the hybrid matcher.
(3) Constructing the ridge feature maps using adaptive methods for optimal selection of the Gabor filters.

With recent advances in fingerprint sensing technology and improvements in the accuracy and matching speed of the fingerprint matching algorithms, automatic personal identification based on fingerprint is becoming an attractive alternative/complement to the traditional methods of identification. We have provided an overview of the fingerprint-based identification and summarized algorithms for fingerprint feature extraction, enhancement, matching, and classification. We have also presented a performance evaluation of these algorithms. The critical factor for the widespread use of fingerprints is in meeting the performance (e.g., matching speed and accuracy) standards demanded by emerging civilian identification applications.

Unlike an identification based on passwords or tokens, performance of the fingerprint-based identification is not perfect. There will be a growing demand for faster and more accurate fingerprint matching algorithms, which can (particularly) handle solid-state sensor images. Some of the emerging applications (e.g., fingerprint-based smart cards) will also benefit from a compact representation of a fingerprint. The design of highly reliable, accurate, and foolproof biometrics based identification systems may warrant effective integration of discriminatory information contained in several different biometrics and/or technologies. The issues involved in integrating fingerprint-based identification with other biometric or non-biometric technologies may constitute an important research topic. As biometric technology matures, there will be an increasing interaction among the (biometric) market, (biometric) technology, and the (identification) applications. The emerging interaction is expected to be influenced by the added value of the technology, the sensitivities of the population, and the credibility of the service provider. It is too early to predict where, how, and which biometric technology would evolve and be mated with which applications. But it is certain that biometrics based identification will have a profound influence on the way we conduct our daily business. It is also certain that, as the most mature and well-understood biometric, fingerprints will remain an integral part of the preferred biometric-based identification solutions in the years to come.

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