AUTOMATIC FINGERPRINT CLASSIFICATION SCHEME USING TEMPLATE MATCHING WITH NEW SET OF SINGULAR POINT-BASED FEATURES

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To my God, Allah *‘azza wa jalla*

Then to my beloved mother, family, and all my friends

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ABSTRACT

Fingerprint classification is a technique used to assign fingerprints into five established classes namely Whorl, Left loop, Right loop, Arch and Tented Arch based on their ridge structures and singular points' trait. Although some progresses have been made thus far to improve accuracy rates, problem arises from ambiguous fingerprints is far from over, especially in large intra-class and small inter-class variations. Poor quality images including blur, dry, wet, low-contrast, cut, scarred and smudgy, are equally challenging. Thus, this thesis proposes a new classification technique based on template matching using fingerprint salient features as a matching tool. Basically, the methodology covers five main phases: enhancement, segmentation, orientation field estimation, singular point detection and classification. In the first phase, it begins with greyscale normalization, followed by histogram equalization, binarization, skeletonization and ends with image fusion, which eventually produces high quality images with clear ridge flows. Then, at the beginning of the second phase, the image is partitioned into 16x16 pixels blocks - for each block, local threshold is calculated using its mean, variance and coherence. This threshold is then used to extract a foreground. Later, the foreground is enhanced using a newly developed filling-in-the-gap process. As for the third phase, a new mask called Epicycloid filter is applied on the foreground to create true-angle orientation fields. They are then grouped together to form four distinct homogenous regions using a region growing technique. In the fourth phase, the homogenous areas are first converted into character-based regions. Next, a set of rules is applied on them to extract singular points. Lastly, at the classification phase, basing on singular points' occurrence and location along to a symmetric axis, a new set of fingerprint features is created. Subsequently, a set of five templates in which each one of them represents a specific true class is generated. Finally, classification is performed by calculating a similarity between the query fingerprint image and the template images using x^2 distance measure. The performance of the current method is evaluated in terms of accuracy using all 27,000 fingerprint images acquired from The National Institute of Standard and Technology (NIST) Special Database 14, which is de facto dataset for development and testing of fingerprint classification systems. The experimental results are very encouraging with accuracy rate of 93.05% that markedly outpaced the renowned researchers' latest works.

ABSTRAK

Pengkelasan cap jari adalah satu teknik untuk mengklasifikasi cap jari kepada lima kelas rasmi iaitu Pusaran, Putaran kiri, Putaran kanan, Lengkungan dan Lengkungan terlangkup berdasarkan ciri-ciri struktur rabung dan titik tunggal. Walaupun terdapat kemajuan setakat ini dalam memperbaiki kadar ketepatan, masalah yang dihadapi dalam menangani cap jari yang kabur masih tidak dapat diselesaikan, terutamanya dalam perkara berkaitan perbezaan besar intra-kelas dan perbezaan kecil inter-kelas. Cabaran yang sama juga dihadapi bagi kualiti imej yang tidak baik termasuk kabur, kering, basah, kontras rendah, terpotong, berparut dan comot. Oleh itu, tesis ini mencadangkan satu teknik pengkelasan baru berdasarkan pemadanan templat menggunakan ciri-ciri utama cap jari sebagai peranti pemadanan. Secara asasnya, kaedah ini meliputi lima fasa utama: peningkatan, segmentasi, anggaran medan orientasi, pengesanan titik tunggal dan klasifikasi. Dalam fasa yang pertama, ia dimulai dengan normalisasi skala kelabu, diikuti dengan penyamaan histogram, binarisasi, pengkerangkaan dan diakhiri dengan gabungan imej, yang akhirnya akan membuahkan imej yang berkualiti tinggi dengan aliran rabung yang jelas. Kemudian, pada permulaan fasa yang kedua, imej dipecahkan kepada blok piksel 16x16 - untuk setiap blok, ambang setempat dikira melalui min, varians dan koheren. Ambang ini kemudian diguna untuk mendapatkan latar depan. Selepas itu, latar depan tersebut diperbaiki menggunakan proses mengisi tempat kosong yang baru dibangunkan. Untuk fasa ketiga, satu topeng yang dipanggil penapis *Epicycloid* digunakan pada latar depan untuk mewujudkan medan orientasi sudut sebenar. Kemudian mereka digabungkan bersama bagi membentuk empat kawasan sekata yang berbeza melalui teknik peningkatan kawasan. Dalam fasa keempat, kawasan yang sekata tersebut ditukarkan kepada kawasan berdasarkan aksara. Ini diikuti dengan penggunaan satu set peraturan untuk mendapatkan titik tunggal. Akhir sekali, semasa fasa klasifikasi, berdasarkan kewujudan titik tunggal di sepanjang paksi simetri, satu set ciri-ciri cap jari baru dijana. Setelah itu, satu set lima templat di mana setiap satunya mewakili satu kelas tulen yang spesifik dihasilkan. Akhirnya, proses klasifikasi dilakukan dengan menghitung persamaan di antara imej cap jari carian dan imej templat menggunakan pengukur x^2. Prestasi kaedah ini dinilai dari aspek ketepatannya dengan menggunakan 27,000 imej cap jari yang diperolehi daripada *The National Institute of Standard and Technology* (NIST) *Special Database 14* yang merupakan satu set data piawai untuk pembangunan dan ujian sistem pengkelasan cap jari. Keputusan eksperimen adalah sangat menggalakkan dengan kadar ketepatan 93.05% yang mana dengan ketaranya mengatasi prestasi kerja terkini penyelidik tersohor.

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LIST OF ABBREVIATIONS

2D	-	Two dimensional
A	-	Arch
AFCS	-	Automatic Fingerprint Classification System
AFIS	-	Automatic Fingerprint Identification System
AHE	-	Adaptive Histogram Equalization
B	-	Blue
BC	-	Bottom Core
CH	-	Character-based Homogenous blocks
D	-	Distance
DB14	-	NIST Special Database 14
DCT	-	Discrete Cosine Transform
DP	-	Delta Point
EF	-	Epicycloid Filter
FBI	-	Federal Bureau Investigation
FC	-	False alarm rate of Cores
FD	-	False alarm rate of Deltas
FVC2002	-	Second International Competition for Fingerprint
G	-	Green
HE	-	Histogram Equalization
HMM	-	Hidden Markov Model
HR	-	Homogenous regions
IT	-	Information Technology
LL	-	Left Loop
MC	-	Miss Rate of Cores
MD	-	Miss Rate of Deltas

NCIC	-	National Crime Information Centre
NIST	-	National Institute of Standards and Technology
P	-	Purple
PCASYS	-	Pattern-level Classification Automation System
R	-	Red
RGT	-	Region Growing Technique
RL	-	Right Loop
S	-	String
SK	-	Skeletonization
SVM	-	Support Vector Machine
TA	-	Tented-arch
TC	-	Top Core
W	-	Whorl
WSQ	-	Wavelet Scalar Quantisation

LIST OF SYMBOLS

S_y	-	Vertical Sobel mask operator
$Coh(i, j)$	-	Coherence value of block (i, j)
Mg_0	-	Desired mean value for determine normalization
Vg_0	-	Desired variance value for determine normalization
Mg	-	Global mean value of fingerprint image
Mn	-	Global mean value of normalized fingerprint image
Vg	-	Global variance value of fingerprint image
$\theta(i, j)$	-	Gradient angle of orientation field
$\|Gr(m,n)\|$	-	Gradient magnitude of pixel (m,n)
$G_x(m,n)$	-	Gradient of pixel (m,n) in horizontal direction
$G_y(m,n)$	-	Gradient of pixel (m,n) in vertical direction
S_x	-	Horizontal Sobel mask operator
$I(m,n)$	-	Intensity value of the pixel at the *m*-th row and *n*-th column in the fingerprint image
$N(m,n)$	-	Intensity value of the pixel at the *m*-th row and *n*-th column in the normalized fingerprint image
$Mb(i, j)$	-	Local mean value of block (i, j)
Nc	-	Number of cores
Nd	-	Number of deltas
$B \times B$	-	Size of block in the fingerprint image
$W \times H$	-	Size of fingerprint image
c	-	Threshold factor for gradient
G_{th}	-	Threshold value for gradient

$V_x(i,j)$	-	Vector gradient x-direction of block (i,j)
$V_y(i,j)$	-	Vector gradient y-direction of block (i,j)
∂	-	Threshold of the Binarization process
Δ	-	Delta
C_i	-	Exclusive Class Of image I
I	-	Image
O	-	Core
φ	-	Angle of the symmetric axis

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CHAPTER 1

INTRODUCTION

1.1 Overview

Biometrics are measurable characteristics based on physiological and behavioural traits that are used in the identification of individuals. The most important type of human biometrics is fingerprints. Fingerprints have been used for personal recognition in forensic applications such as criminal investigation tools and in civilian applications, as well as border access control systems, national identity card validation and authentication processors. The uniqueness and immutability of fingerprint patterns as well as the low cost of associated biometric equipment make fingerprints more desirable than the other types of biometrics (Maltoni and Cappelli, 2009). Fingerprints develop during the fourth or the fifth month after conception. The pattern of a person's fingerprints remain much the same until his death, or until he gets injured in an accident. Age of a person does not change a person's fingerprints but injury does. Schaeuble J (1932) and Babler W (1991) had proven that fingerprints of twins sharing similar DNAs are different. Fingerprint biometric identification is low-cost because it involves pattern recognition using IT equipment and does not require laboratory wet tests (such as blood test) Kücken M., and Newell A. C (2004).

Generally, fingerprint-based recognition systems work in two modes: verification and identification. In verification mode, the systems verify the person's identity using a 1:N comparison between the person's fingerprints and those stored in the record. Verification process confirms whether the identity of the person with the fingerprint is the valid person. However, the process used in fingerprint identification systems is more complex than the process employed in print verification especially for large databases because fingerprint identification requires the input fingerprints to be compared with all the fingerprints in the database to find a match. While verification uses 1:1 comparison for matching, fingerprints identification requires 1:N comparison to establish if the individual is present in the database (Maltoni *et al.*, 2005).

In fingerprint identification, both matching accuracy and processing time are critical issues. To achieve an efficient identification of a fingerprint, fingerprints in the database are organized into a number of mutually exclusive classes that share certain similar properties. This process is called fingerprint classification. In order to design an automatic system for identification which has better accuracy, pre-processing of the fingerprints have to be carried out to enhance and extract the fingerprint features (Wu *et al.*, 2007).

1.2 Background of Research

The most important part of an Automatic Fingerprint Identification System (AFIS) is the fingerprint classification because it provides an indexing mechanism and facilitates the matching process with the large databases. When a class of a query fingerprint is known, matching the fingerprint only requires that the print is compared with a similar class of prints.

Evidence suggests that people were aware of the presence of fingerprints in ancient times. However, there is no indication that anyone recognised the full potential of fingerprints as a means of personal identification (Yager and Amin, 2004a). Sir Francis Galton (1892) was the first person to study of fingerprint-based identification. Among many contributions to the field, his work led to the first formally recognized system for fingerprint classification. Galton's classification was introduced as a means of indexing fingerprints in order to facilitate the search for a particular fingerprint within a collection of many prints and proposed three basic fingerprint classes: the Arch, the Loop, and the Whorl shown in Figure 1.1. Galton's other major contribution was the first study into the uniqueness of fingerprints. In addition to permanence, uniqueness is also necessary for a fingerprint to be a viable method of personal identification.

Figure 1.1 Examples of Galton's three classes (Maltoni, 2009)

Building on Galton's work, Edward Henry (1990) subdivided two of the three main classes into more specific sub-classes. Henry distinguished between the Arch, Tented-arch, Left Loop, Right Loop and the Whorl, as shown in Figure 1.2. He also introduced the concept of fingerprint ''Core'' and ''Delta'' points and used them as aids for fingerprint classification. Henry's classification scheme constitutes the basis for most modern classification schemes (Yager and Amin, 2004).

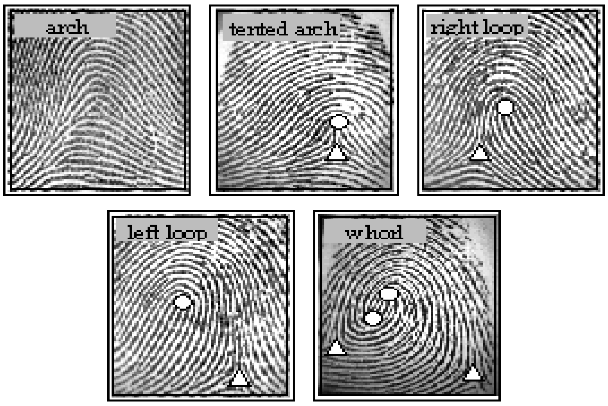


Figure 1.2 An example of Henry's five classes (Yager and Amin, 2004)

The distribution of the classes in nature is not uniform. The probabilities of the classes are approximately $3.7\%, 2.9\%, 33.8\%, 31.7\%$ *and* 27.9% for the Arch, Tented-arch, Left Loop, Right Loop, and Whorl, respectively (Jain *et al.*, 1999; Wilson *et al.*, 1994). Left Loop, Right Loop and Whorl are the most common, making up 93.4% of all fingerprints (Yager and Amin, 2004). To develop and test a classification system, it is important to use a suitable dataset with a large enough sample size that is representative of the natural distribution of human fingerprint classes in the population. However, most researchers so far have used the National Institute of Standard and Technology NIST database 4 which provided an insufficient sample size (less than 10,000 prints) for testing and validating their experiments (Jain *et al.*, 1999; Jain *et al.*, 2002; Hou *et al.* 2008; Wang and Xie 2004.). Thus, the validity of their experimental results is disputable, and the performance of their proposed classification methods implausible. As a result of these limitations, the NIST Special Database 14 was created and became the de facto standard dataset for developing and testing of automatic fingerprint classification systems (Maltoni and Cappelli., 2009).

Unfortunately, there are still a number of remaining issues related to fingerprint classification. These include the challenge of classifying ambiguous fingerprint which cannot be easily classified, even by human experts, because these fingerprints have properties that fall into more than one class (see Figure 1.3(a) – (f)). Of the 27,000 fingerprint images contained in NIST special Database 14, about 6.63 percent are ambiguous. Under this condition, which fingerprint classes these ambiguous prints should be matched against is very uncertain (Maltoni and Cappelli, 2009).

(a) File name (F0000077) (b) File names (F0000429) (c) File names (F0000233)

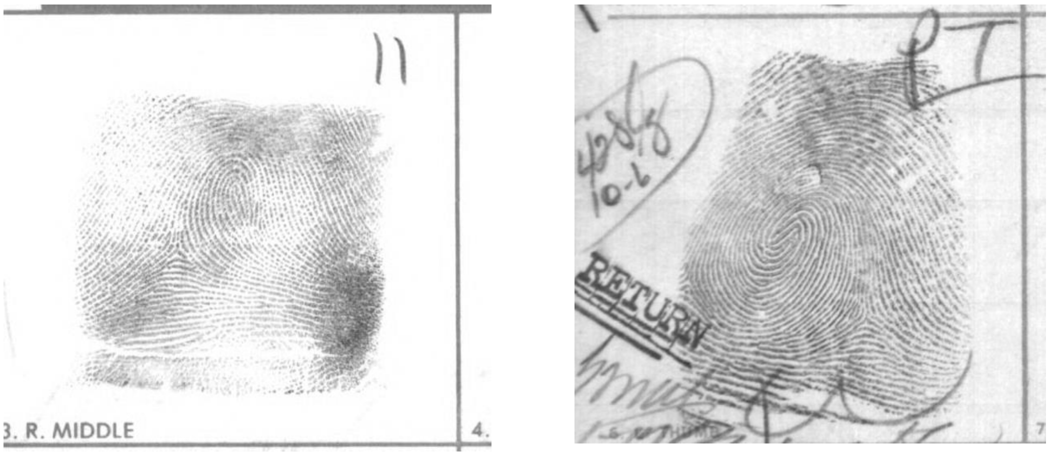
(d) File names (F0021127) (e) File name F0021722 (f) File name (F0022002)

Figure 1.3 Examples of ambiguous fingerprints found in NIST special Database 14: (a) Image with Arch and Tented-arch classification; (b), (c) and (d) Images with Whore and Right Loop classification; (e) Image with Right loop and Tented-arch classification; (f) Image with Left loop and Tented-arch classification

Another difficulty that makes fingerprint classification so problematic is that the sample of fingerprint images is of poor quality due to injuries or scars which many applications end up rejecting. For this reason, to improve classification accuracy, the images are first enhanced through reconstruction. A rejection procedure is used for those images that cannot be classified. If this is the case, such images will be captured under the classification “unknown” (as shown in Figure 1.4).

Figure 1.4 An example of a scar fingerprint image (F0002119) found in NIST special Database 14

The noise in the fingerprint image which brings about misclassification can be generated by both ink and live scans. For ink scans, the noise is created by too much ink or by insufficient use of ink during the fingerprint imprinting process. During live scans, the noise is caused by either dry or wet prints depending on the surface of the skin (oily, clammy, sweaty, and so on). The NIST Special Database 14 contains images that are often tainted by signatures and handwriting of human experts (see Figure 1.5). These signatures and comments are referred to as noise and require manual pre-processing to remove annotations and artefacts (Maltoni and Cappelli, 2009). These occurrences are considered non-automatic because of human involvement, and should be avoided if possible. However, developing a full-scale automatic fingerprint classification system is a very challenging task.



(a) (b)

Figure 1.5 Examples of problematic fingerprints found in NIST special Database 14 (a) A dry image (b) Image containing hand written annotations

Most classification schemes use five classes. Any significant similarities in the structure and shape of human fingerprints creates difficulty in distinguishing and differentiating orientation patterns of ridge structure within the same class, especially in Whorl cases (see Figure. 1.6). These difficulties and problems are associated with large intra-class variation, where the prints of the same class can have similar characteristics covering a large spread, and are therefore difficult to classify (Wang *et al.*, 2007). This intra-class problem is extremely difficult to deal with even for human experts.

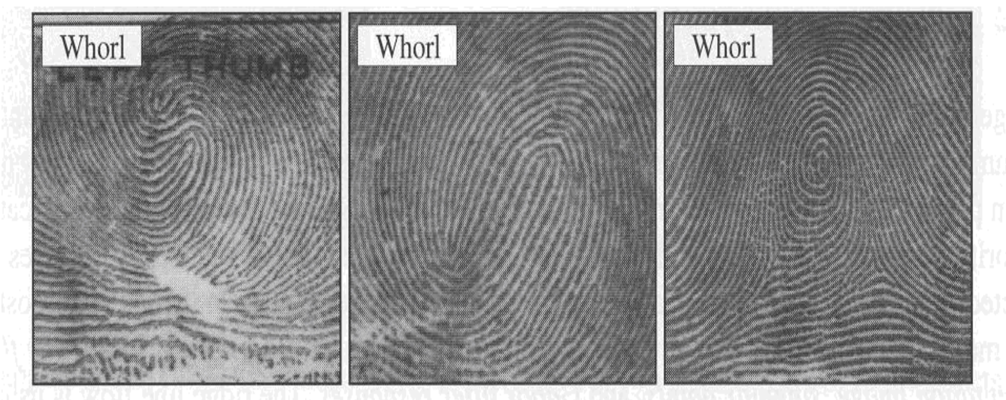


Figure 1.6 Three fingerprints of the same class that have very different characteristic (large intra-class variability) (Wang *et al.*, 2007)

Generally speaking, a fingerprint image contains two features, which are the global feature and the local feature. The global features of the fingerprint image are described by structure shapes (ridges and valleys) and a singular points (core and delta) as shown in Figure 1.7. The local features of the fingerprint consist of minute ridge details. These global features contain global information that is considered valid in the design of automatic fingerprint identification systems (Jain *et al.*, 1999). Therefore, it makes sense to derive these features directly from the fingerprint ridges. Orientation field estimation is a convenient way to represent the global ridge structure of fingerprints. Although orientation field estimation is the best approach to represent ridge structures, there are still many challenges regarding the classification of low quality images.

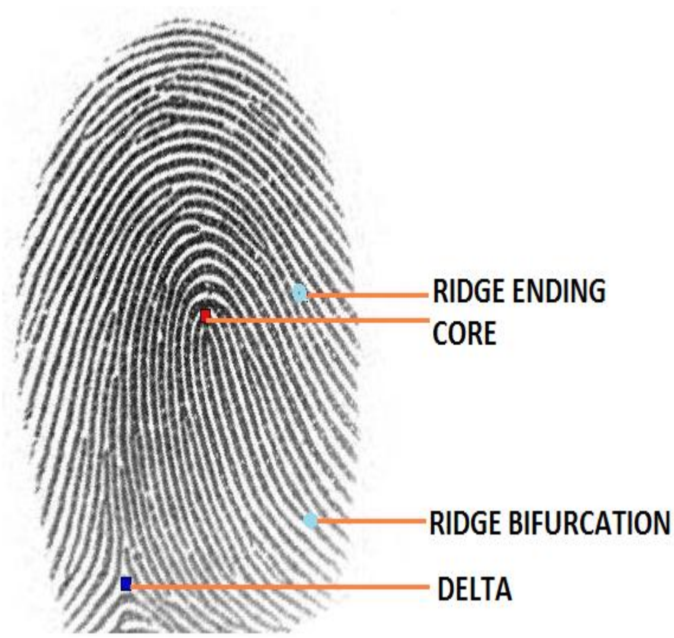


Figure 1.7 Ridge and valley structures and singular points

Another global feature often used by researchers to distinguish fingerprint classes is the presence and location of singular points. The singular points of fingerprint image are represented by "Core" and "Delta" points that appear in singularity-based patterns. Some of the difficulties faced by singularity-based patterns are that singular points may not be visible in the image (Kumar *et al.*, 2011).

This is especially true if the image has poor quality, or if the image contains a high level of noise. This makes the extraction of a singular point in the fingerprint unreliable. Researchers have proposed different methods to locate singular points. The most common and widely used approach is the Poincaré Index (Mandal *et al.*, 2013). However, there are a number of limitations, such as a high sensitivity to noise, and its difficulty capturing low contrast and low quality fingerprint images (Hsieh *et al.*, 2005).

These performance limitations necessitate continued research in this area. In an effort to mitigate the identified challenges, the following research questions guide this study:

1. How to accurately and optimally classify the fingerprint based on five classes?
2. How to improve quality of image having poor quality?
3. How to automatically extract foreground from the background?
4. How to locate and remove the noise to improve the quality of the image?
5. How to estimate the orientation fields of the images having poor quality?
6. How to precisely detect the genuine singular points?
7. How to classify ambiguous fingerprints such as intra- and inter-class variations?

1.3 Problem Statements

Based on the problem background and research questions, the issues to be resolved are:

1. Fingerprint images from the NIST Special Database 14 are raw data of various qualities: clear, blur, smudgy, wet, dry, scarred, cut and low-contrast (Jain *et al.*, 1997; Maltoni and Cappelli, 2009; Sulong, *et al.*, 2009; Saparudin, 2012). Apart from that, almost all images contain

human expert hand written annotations that further deteriorate the prints. Therefore, it is crucial to make them good by enhancing their quality while still preserving the actual ridge flow.

2. The fingerprints either have non-ridge regions on a background, or they have ridge regions but with foreground containing unwanted hand written comments and references. In the past these images were cropped manually to extract foreground from background manually, which was very labour-intensive. Later, a couple of studies automate the process (Maltoni *et al*. 2009; Saparudin, 2012). However, their works are far from over. Thus, In order to design a fully automated system, it is necessary to implement a more robust method of segmentation to extract the image's foreground from the background and also frees from artefacts and unwanted annotations.

3. Ridge patterns in a fingerprint follow a certain field structure. This structure can be represented in the form of orientation field estimation patterns. In previous studies, researchers have used pre-defined angles (for example 0, 45, 90, 135 and 180 degrees) to represent the original ridge shape orientation of fingerprint images (Ratha *et al.*, 1995; Hsieh *et al.*, 2005; Zhang *et al.*, 2007). However, these pre-defined angles do not always represent the actual ridge orientation. For that reason, it is necessary to improve the computability of the original ridge orientation and the digital smoothing of the orientation field estimation process.

4. The Poincaré Index is considered a robust technique to locate singular points, and its performance relies heavily on the quality of orientation fields (Maltoni and Cappelli, 2009). However, a number of researchers have customized the index for their experiments and directly employed a simplified Poincaré Index to determine singular points without subjecting the fingerprints to a filtering process, which often resulted in false singular points (Zhang and Yan, 2004). Consequently, a more efficient method is necessary to suggest for detecting a genuine singular point.

5. In case of ambiguous prints, more than one class of fingerprints is present that and cannot be easily classified by human experts, let alone by computer. In fact, about 6.63 percent of the 27,000 images in the NIST Special Database 14 are ambiguous. In these cases, it is unclear which fingerprint classes the ambiguous prints should be matched against. Furthermore, these ambiguous prints are also susceptible to inter-class variation, particularly in Arch and Tented-arch cases. Some Tented-arch prints closely resemble the traditional arch shape (i.e. the peak of the Tented-arch is unnoticeable due to defective or deformed vertical shapes). Therefore, it is necessary to come up with solution to this issue (Maltoni and Cappelli, 2009).

6. Large intra-class variation remains a key occurrence that prevents correct classification of the Whorl class, as mentioned by (Maltoni and Cappelli., 2009; Saparudin, 2012).

7. Scars on fingerprints can be caused by accidents, injuries, long exposure to detergents or chemicals, or hard labour. Most scarred prints contain patterns of some parts of the epidermis which have been damaged and consequently distort the original ridge structure of fingerprints. Therefore, many applications reject such images (Maltoni *et al.*, 2009; Saparudin, 2012). Though, the scarred prints percentage found in the NIST Special Database 14 is negligible, it is worth to investigate because in reality there exist a significant number of such prints that require special attentions and specialised tools to correct the damage (Sulong, *et al.*, 2009).

1.4 Research Goal

To develop a fully automated fingerprint classification system or AFCS in short that performs with a higher degree of accuracy than is currently available. The

AFCS will be able to classify most fingerprint images with varied quality. It does so by using pre-processing procedures which execute image enhancement, foreground segmentation, orientation field estimation and singular point detection.

1.5 Objectives of the Study

In order to achieve the above mentioned goal, the following objectives will be fulfilled:

1. Improve the quality of defective images in the fingerprint dataset by using improved reconstructive enhancement techniques.

2. Develop new techniques that identify and detect unwanted objects (hand writing comment and signature) in the fingerprint dataset, and extract the image foreground from the background.

3. Introduce a new orientation field estimation method that utilizes the true angle of the orientation fields in accordance with the natural gradient of a print's ridge structure.

4. Propose a new singular point detection technique that able to minimize the number of inaccurate Core and Delta points.

5. Design and implement a new reliable fingerprint classification approach to classify all 27,000 fingerprint images of NIST Special Database 14, including scarred prints, into five exclusive classes: Whorl, Left loop, Right loop, Arch and Tented-arch.

1.6 Research Scope

This study is a synthesis of a complete process of automatic fingerprint classification which includes the introduction of an effective fingerprint enhancement, a novel approach to fingerprint segmentation, optimal orientation field estimation, accurate singular point detection, and ultimately, a reliable fingerprint classification method.

This system will be tested using a standard dataset testing platform, employing grey-scale fingerprint images obtained from the NIST special fingerprint database 14. The database contains 54,000 8-bit grey-scale images of rolled fingerprint impressions that were scanned from 27,000 individuals. This study uses the latest work of Saparudin (2012) as a baseline which has already shown results superior to those of Maltoni's (2009) work. Identical fingerprint samples (f0000001 to f0027000 prints) that were used by Saparudin (2012) will also be used for all tests in this study. In order to confirm the improved performance of this system, scarred prints will also be included.

It is observe that normal practices of the previous works; efficiency is only measured by class assignment's accuracy without bothering the processing time, this study, therefore, will follow the norm.

1.7 Significance of the Study

It is hoped that the proposed fully automated fingerprint classification system AFCS will overcome the challenges of existing fingerprint classification as a consistently reliable biometric system. The AFCS may do so by reducing ambiguity error, minimize problems associated with poor quality images, and large intra-class variation. Existing fingerprint classification studies have shown some encouraging results with success rates greater than 94 percent. However, these results, as well as employed methods are disputable because the datasets used were from NIST 4 which contains fingerprint patterns that have already been cleaned and any existing noise removed from the background. In industrial and forensic applications the fingerprints that are collected are naturally flawed. That that reason, more rigorous testing using a higher level dataset such as the NIST Special fingerprint database 14 is necessary to confirm that a more elaborate procedure can be used effectively for industrial and forensic purposes. Manual processes are time consuming and tedious and less suitable for a real life applications.

In light of the above mentioned issues, results of this research will contribute to what is currently known about fingerprint classification systems. Nonetheless, the significance of this study is not only limited to knowledge enrichment.

1.8 Thesis Outline

This thesis includes five chapters: The introductory chapter, a review of some of the relevant literatures to date, research methodology, experimental results, and the conclusion. Some of the topics reviewed are enhancement, segmentation, orientation field estimation, singular point detection, and classification of fingerprints.

The methodology chapter describes in detail the proposed automatic fingerprint classification method including fingerprint image enhancement, image segmentation, orientation field estimation, singular point detection, symmetric axis calculation and the template-based classification approach.

The results and discussion chapter describes the experimental setting, gives details about the conducted performance evaluations, and the implementation results of image segmentation, enhancement, orientation field estimation, singular point detection, and new classification of fingerprints.

The conclusion chapter discusses the remaining unresolved issues, objectives and proposed approaches, and ends with highlighting the achievements and suggestions for future work.

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