AN AUTOMATIC FINGERPRINT CLASSIFICATION TECHNIQUE BASED ON SINGULAR POINTS AND STRUCTURE SHAPE OF ORIENTATION FIELDS

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A thesis submitted in fulfilment of the
requirements for the award of degree of
Doctor of Philosophy (Computer Science)

Faculty of Computer Science and Information System
Universiti Teknologi Malaysia

JULY 2012

To my God, Allah *‘azza wa jalla*

Then to my beloved mother, wife, children, and parent-in law

ACKNOWLEDGEMENTS

Thanks to Allah SWT for everything I was able to achieve and for everything I tried but I was not able to achieve.

I am grateful for several people for making this thesis possible. I would like to begin by expressing my deep appreciation to my supervisor, Professor Dr. Ghazali bin Sulong for his guidance and encouragement. Despite the busy schedule, he has provided me with valuable ideas, advice and comments. I am very fortunate to have him as my adviser. I would like to thank Dr. Darmawijoyo and Dr. Yusuf Hartono for personal support.

I would like to thank my wonderful wife for understanding and love. You are always there when I needed support. You are the only reason I worked hard.

ABSTRACT

Generally, an automatic fingerprint classification system aims to classify the fingerprints into several categories based on global features such as ridge structure and singular points. Its process basically covers: segmentation, enhancement, orientation field estimation, singular point detection, and classification. However, its performance is heavily relied on image quality that comes in various forms such as low contrast, wet, dry, bruise, cuts, stains, etc. Although a great effort has been made by previous studies to come out with various methods, their performances especially in terms of accuracy are fallen short, and room for improvements is still wide open. Thus, this thesis proposes an automatic fingerprint classification scheme based on singular points and structural shape of orientation fields. This method begins with foreground extractions using a composite method which combines local mean values of the grey-levels with local variances of the gradient magnitudes. Then, noise patches in the foreground are detected using coherence, and are enhanced using minimum variance of gradient magnitude. Next, Least Mean Square algorithm is applied to estimate the orientation fields, and a corrective procedure is performed on the false ones using minimum variance of the orientation fields. Later, an orientation image is created, and then partitioned into several distinct regions of homogenous orientation fields. The convergence point of these regions implicitly reveals an area that most likely contains a singular point. Subsequently, core and delta in this localized area are then detected using the Poincaré index. Finally, based on the number of core and delta and their locations, an exclusive membership of the fingerprint can be ascertained. Should it fail, the structure shape of the orientation fields neighbouring the core or delta is analysed. The performance of the proposed method is evaluated and tested using 27,000 fingerprints of NIST Special Database 14, which is considered de facto standard dataset for development and testing of fingerprint classification systems. The results obtained are very encouraging with accuracy rate of 89.31% that markedly outperformed the latest work of the renowned researchers.

ABSTRAK

Secara umumnya, sistem klasifikasi cap jari automatik bertujuan untuk mengklasifikasikan cap jari ke dalam beberapa kategori berasaskan kepada ciri-ciri global seperti struktur rabung dan titik singular. Prosesnya meliputi: segmentasi, peningkatan, anggaran bidang orientasi, pengesanan titik singular, dan klasifikasi. Walau bagaimanapun, prestasinya amat bergantung kepada kualiti imej yang berasal dari pelbagai bentuk seperti kontras rendah, basah, kering, luka, noda, dan sebagainya. Walaupun usaha gigih telah dibuat oleh kajian sebelumnya untuk menghasilkan pelbagai kaedah, prestasinya terutamanya dari segi ketepatan adalah kurang memberangsangkan, dan ruang untuk penambahbaikan masih terbuka luas. Oleh itu, tesis ini mencadangkan skim klasifikasi cap jari automatik berdasarkan titik singular dan bentuk struktur bidang orientasi. Kaedah ini bermula dengan pengekstrakan latar-depan dengan menggunakan kaedah komposit yang menggabungkan nilai min tempatan tahap kelabu dengan varians tempatan magnitud kecerunan. Kemudian, tompokan hingar latar-depan dikesan menggunakan koherensi dan dipertingkatkan menggunakan varians minimum magnitud kecerunan. Selepas itu, algoritma min kuasa dua terkecil digunakan untuk menganggarkan bidang orientasi, dan prosedur pembetulan dilakukan terhadap bidang orientasi yang palsu dengan menggunakan varians minimum bidang orientasi. Kemudian, orientasi imej diwujudkan, dan seterusnya dipecahkan kepada beberapa kawasan yang berbeza mengikut bidang orientasi yang homogen. Titik penumpuan kesemua kawasan ini secara tersirat mendedahkan kawasan yang paling mungkin mengandungi titik singular. Selanjutnya, teras dan delta dalam kawasan setempat ini dikesan dengan menggunakan indeks *Poincaré*. Akhirnya, berdasarkan bilangan teras dan delta serta lokasinya, keahlian eksklusif cap jari boleh ditentukan. Sekiranya gagal, bentuk struktur bidang orientasi yang berjiran dengan teras atau delta dianalisis. Prestasi kaedah yang dicadangkan ini dinilai dan diuji dengan menggunakan 27,000 cap jari daripada Pangkalan Data Khas NIST 14, yang dianggap sebagai set data piawai untuk pembangunan dan ujian sistem pengkelasan cap jari. Keputusan yang diperolehi adalah sangat menggalakkan dengan kadar ketepatan 89.31% yang ketara mengatasi prestasi kerja terbaru dari penyelidik tersohor.

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LIST OF ABBREVIATIONS

FBI	-	Federal Bureau Investigation
AFIS	-	Automatic Fingerprint Identification System
AFCS	-	Automatic Fingerprint Classification System
NIST	-	National Institute of Standards and Technology
NN	-	Neural Network
HMM	-	Hidden Markov Model
2D	-	Two dimensional
DMF	-	Directional Median Filter
DB14	-	NIST Special Database 14
SVM	-	Support Vector Machine
FVC2002	-	Second International Competition for Fingerprint Verification Algorithm
CCB	-	Cross Centre Block
BoI	-	Block of Interest
CB	-	Convergence Block
CRSP	-	Candidate Region Singular Point
GoB	-	Group of Block
CoB	-	Combination of Block
NCIC	-	National Crime Information Centre
WSQ	-	Wavelet Scalar Quantisation
MC	-	Miss Rate of Cores
MD	-	Miss Rate of Deltas
FC	-	False alarm rate of Cores
FD	-	False alarm rate of Deltas
MSE	-	Mean Square Error

LIST OF SYMBOLS

$I(m,n)$	-	Intensity value of the pixel at the *m*-th row and *n*-th column in the fingerprint image
$W \times H$	-	Size of fingerprint image
Mg	-	Global mean value of fingerprint image
Vg	-	Global variance value of fingerprint image
$N(m,n)$	-	Intensity value of the pixel at the *m*-th row and *n*-th column in the normalized fingerprint image
Mg_0	-	Desired mean value for determine normalization
Vg_0	-	Desired variance value for determine normalization
Mn	-	Global mean value of normalized fingerprint image
$B \times B$	-	Size of block in the fingerprint image
$Mb(i,j)$	-	Local mean value of block (i,j)
$G_x(m,n)$	-	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
S_y	-	Vertical Sobel mask operator
$\lvert Gr(m,n) \rvert$	-	Gradient magnitude of pixel (m,n)
G_{th}	-	Threshold value for gradient
c	-	Threshold factor for gradient
$Mgr(i,j)$	-	Local mean value of gradient magnitude of block (i,j)
$Vgr(i,j)$	-	Local variance value of gradient magnitude of block (i,j)
$Coh(i,j)$	-	Coherence value of block (i,j)
$V_x(i,j)$	-	Vector gradient x-direction of block (i,j)
$V_y(i,j)$	-	Vector gradient y-direction of block (i,j)

$V_z(i, j)$	-	Vector gradient resultant direction of block (i, j)
D	-	Set of gradient magnitude in CCB
D_i	-	Subset *i*-th of gradient magnitude in CCB
$Mgm\|D_i$	-	Mean value of subset *i*-th of gradient magnitude in CCB
$Vgm\|D_i$	-	Variance value of subset *i*-th of gradient magnitude in CCB
P	-	Set of normalized fingerprint image in CCB
P_i	-	Subset *i*-th of normalized fingerprint image in CCB
$Mi\|P_i$	-	Mean value of subset *i*-th of normalized fingerprint image in CCB
Q	-	Set of gradient angle in CCB
Q_i	-	Subset *i*-th of gradient angle in CCB
$Ma\|Q_i$	-	Mean value of subset *i*-th of gradient angle in CCB
$Va\|Q_i$	-	Variance value of subset *i*-th of gradient angle in CCB
$Gs(p,q)$	-	Gaussian filtering mask
$\theta(i, j)$	-	Gradient angle of orientation field
$\delta(k)$	-	Closed-curve angle
PI	-	Poincaré index in continuous vector
$P(i, j)$	-	Poincaré index in discrete vector
Nc	-	Number of cores
Nd	-	Number of deltas

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Biometric is automatic recognition of a person that is based on physiological measurements or behavioural traits. Fingerprint as a kind of human biometric features has been used for over a century and the most widely used for personal recognition in civil, forensic, and commercial areas because of its uniqueness, immutability, reliability, and low cost. For example, the total number of fingerprint cards where each card contains one impression for each of the 10 fingers of a person in the FBI fingerprint database stands well over 200 million from its original number of 810,000 and is growing continuously (Maltoni *et al*., 2009). The uniqueness of fingerprint has been studied and it is well established that the probability of two fingerprints matching is vanishingly small (Jain *et al*., 2000; Pankanti *et al*., 2002). The immutability of fingerprint is persistent with age and can not be easily disguised (Yager and Amin, 2004).

Generally, a fingerprint recognition system works in two modes: verification or identification, depend on the application and the requirement. In the verification mode, the user inputs fingerprint and claims identity information, then the system verify whether the query fingerprint is consistent with the claimed identity. In the identification mode, the user only inputs fingerprint and the system needs to identify the potential corresponding fingerprints from the database without the claimed identity information. Fingerprint identification needs to search the entire database to find the potential corresponding ones to the query fingerprint. The huge amount of data of the large fingerprint databases seriously compromises the efficiency of the identification task, although the fastest matching algorithms take only a few milliseconds per matching.

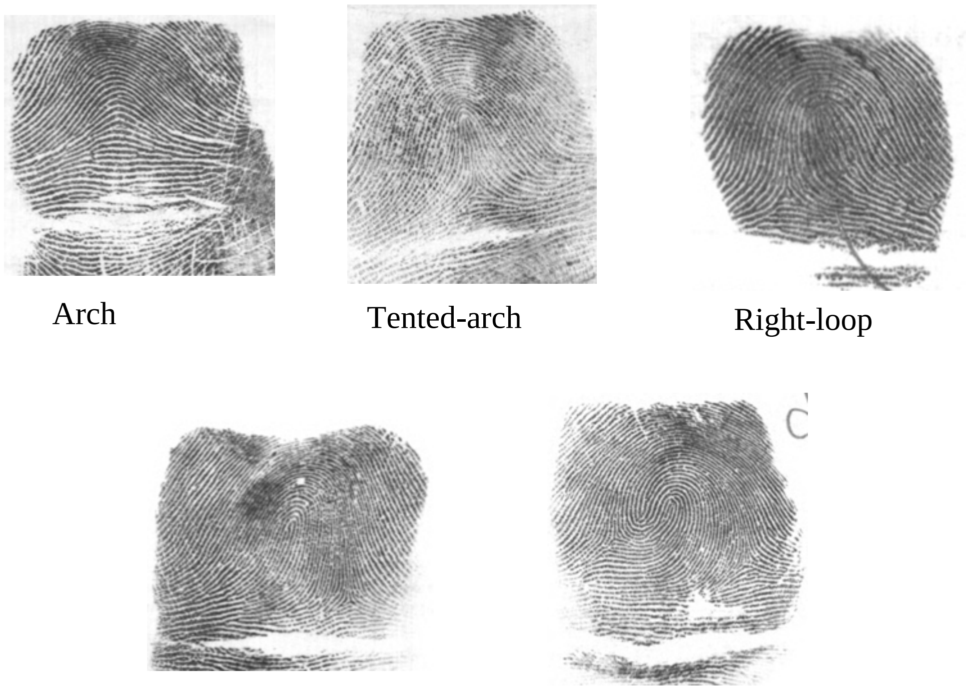
To perform fingerprint identification, both matching accuracy and processing time are critical performance issues. In order to achieve an efficient identification of a fingerprint, fingerprints in the database are organized into a number of mutually exclusive classes that share certain similar properties. This process is called fingerprint classification. Therefore, although all automatic fingerprint identification system require the fingerprint classification stage before the matching stage, it is very difficult to design an automatic system able to perform such classification with high accuracy (Karu and Jain, 1996).

1.2 Background of Research

Fingerprint classification is an important stage in automatic fingerprint identification system (AFIS) because it significantly reduces the processing time to search and retrieve in a large-scale fingerprint database (Cappelli *et al*., 1999). When a class of a query fingerprint is known, matching the fingerprint only requires the comparison to be done within the class similar to the query fingerprint.

Galton (1892) began the first rigorous study of fingerprint-based identification. Among many contributions to the field, his work contained the first system for fingerprint classification. Classification was introduced as a means of indexing fingerprints in order to facilitate searching for a particular fingerprint within a collection of many prints. He proposed three basic fingerprint classes: the arch, the loop, and the whorl. Galton’s other major contribution was the first study into the uniqueness of fingerprints. In addition to permanence, uniqueness is the other necessity for fingerprints to be a viable method of personal identification.

Several years later Henry (1990) continued Galton's work on fingerprint classification. Henry subdivided the three main classes into more specific subclasses, namely, Arch, Tented-arch, Left-loop, Right-loop and Whorl as shown in Figure 1.1. 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.



Arch Tented-arch Right-loop

Left-loop Whorl

Figure 1.1 Example of five classes

The distribution of the classes in nature is not uniform. The probabilities of the classes are approximately 0.037, 0.029, 0.338, 0.317, and 0.279 for the Arch, Tented-arch, Left-loop, Right-loop, and Whorl, respectively (Wilson *et al.*, 1993). Left- loop, Right-loop and Whorl are the most common, making up 93.4% of all fingerprints. Therefore, for developing and testing of a classification system, it is important to use a suitable dataset with sufficient sample size that can represent natural distribution of human fingerprints' classes. However, most researchers employed NIST database 4 and insufficient samples (i.e. less than 10,000 prints) for testing and validating their experiments (Karu and Jain, 1996; Hong and Jain, 1999; Jain and Minut, 2002; Zhang and Yan, 2004; Wang and Xie, 2004; Wang and Dai, 2007). Thus, their experimental results' validity is disputable, and consequently the performance of their proposed classification methods is also implausible (Maltoni *et al.*, 2009). In relation to that, NIST Special Database 14 was created and becomes de facto standard dataset for developing and testing of automatic fingerprint classification systems (Watson, 1993; Maltoni *et al.*, 2009).

Naturally, there are some fingerprints that are ambiguous and can not be classified even by a human expert because in some cases, the fingerprints have properties more than one classes (see Figure 1.2). There is about 3.39% of the 27,000 images in the NIST Special Database 14 have two different ground truth labels (Cappelli and Maltoni, 2009). In these cases it is unclear which fingerprint classes the ambiguous prints should be matched against.

(a) (b)

Figure 1.2 Samples of ambiguous prints

Fingerprint images of poor quality due to scars and injuries are often difficult to classify, even for a human expert: in many applications such images are rejected (Figure 1.3). Because this would be less damaging than a wrong decision. For this reason, to improve the accuracy, several classification approaches apply a rejection mechanism in which the images are classified as "unknown".

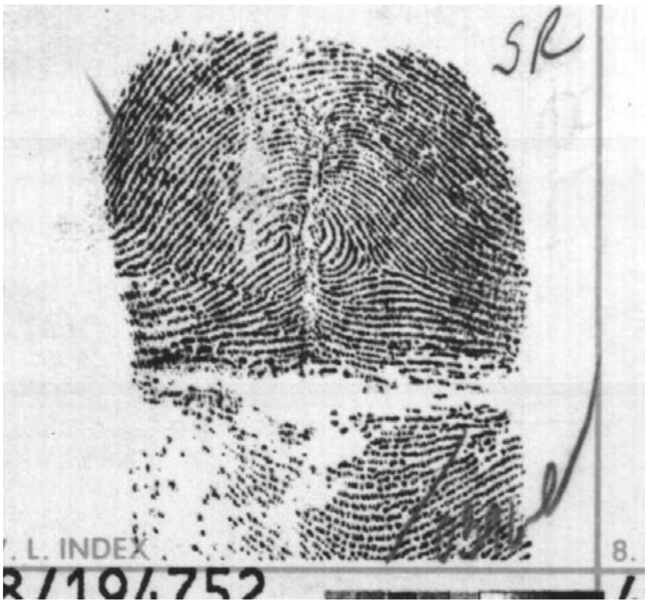
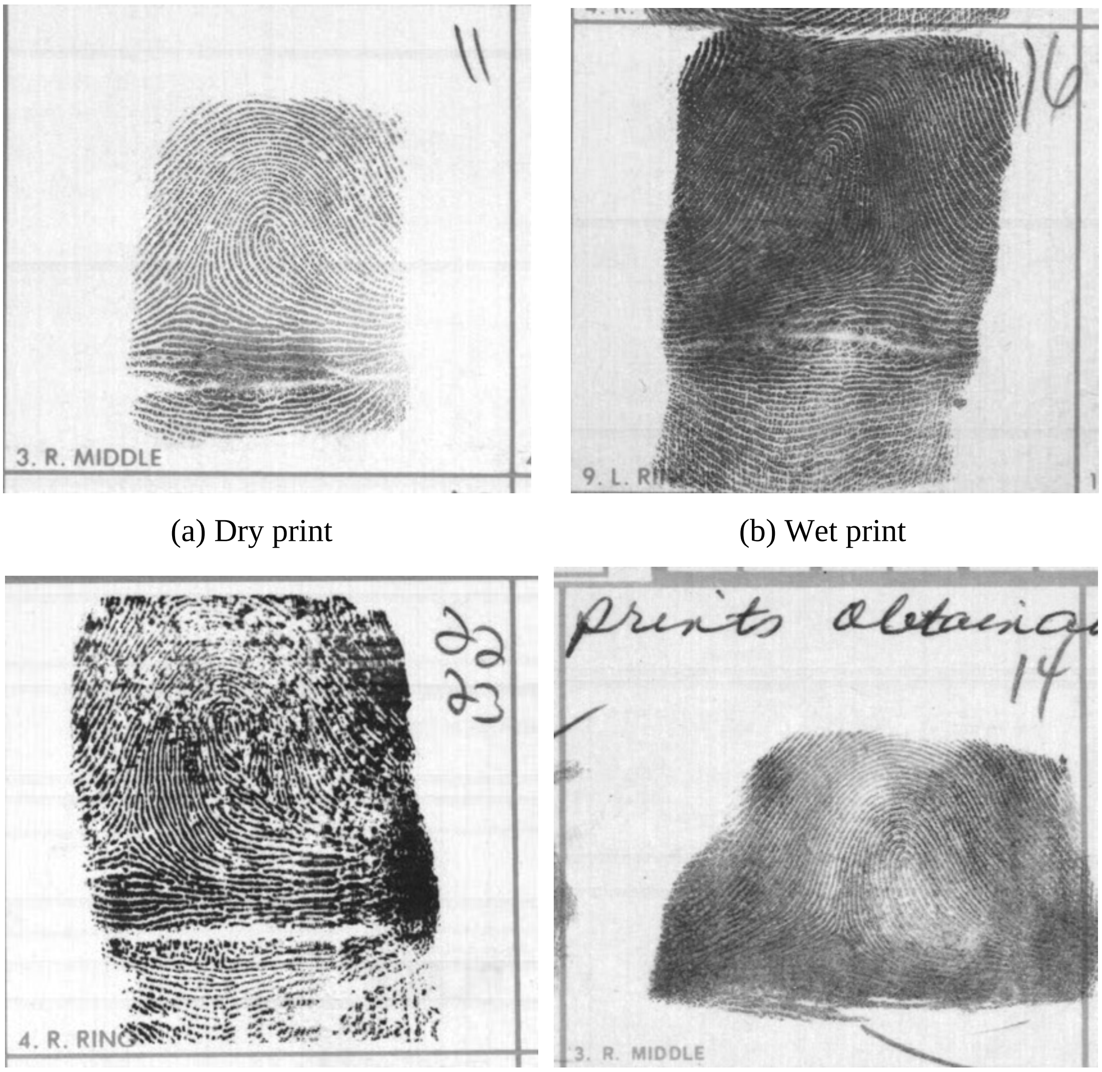


Figure 1.3 Rejected prints

There is always the possibility of misclassification due to noise especially generated by excessive or insufficiently used of ink during fingerprint imprinting process. In relation to that, there are many dry, wet and bruises prints existed in the NIST Special Database 14 that is considered of unfavourable quality. The database also contains images that are often tainted by handwritten annotations and other artefacts common to inked fingerprints (see Figure 1.4). Generally, manual cropping of fingerprint images is a commonly used pre-processing in order to remove the annotations and artifacts (Cappelli and Maltoni, 2009). Besides, cropping and alignment are also manually applied for extracting and realignment of a foreground image. A foreground of size 500×500 pixels and in upright position is more preferable as a work area by most researchers. However, the above processes are considered non-automatic because of human intervention, and should be avoided if possible. Therefore, developing a full scale automatic fingerprint classification system is considered a very challenging task.



(a) Dry print (b) Wet print

(c) Bruises print (d) Tainted print

Figure 1.4 Dry, wet, bruises and tainted prints

The majority of classification schemes use five classes. However, there is a large distinction among orientation patterns of ridge structure within the same class, especially in the whorl case (see Figure 1.5(a)). This problem is usually termed as large-intra-class variation, in which the prints of the same class have distinct characteristics causing the similarity measure having to cover large spread, and therefore is difficult to classify (Li *et al.*, 2007). Moreover, in some cases, prints from one class can appear very similar to prints from another class, particularly arch and arch-like classes (i.e. Left-loop, Tented-arch and Arch). In other words, there is a small-inter-class variation (see Figure 1.5(b)). This interclass problem is extremely difficult to deal even for a human expert.

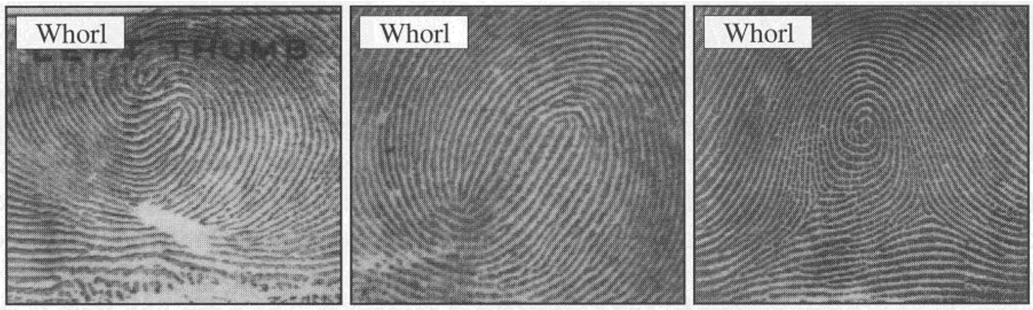


Figure 1.5(a) Three fingerprints of the same class that have very different characteristic (large-intra-class variability). (Source: NIST Special Database 14)

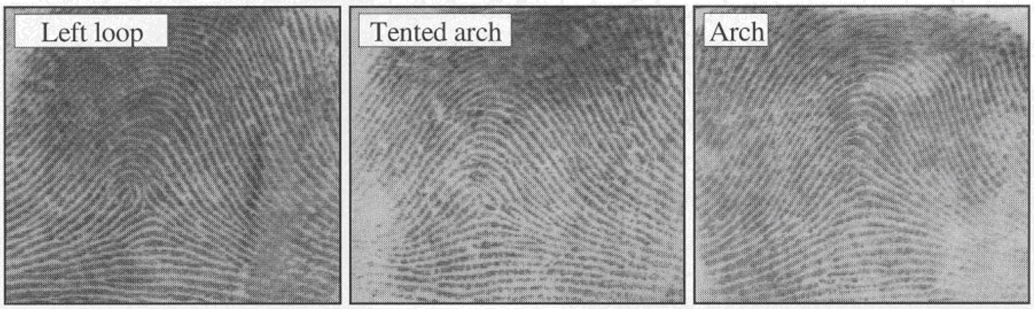


Figure 1.5(b) Three fingerprints belonging to different classes that have similar appearance (small-inter-class variability). (Source: NIST Special Database 14)

Choosing the distinguishable features is very important for the fingerprint classification that affects its performance. The category of a fingerprint is determined by its global ridges and valleys structures as shown in Figure 1.6. There are two kinds of features for its representation: global features that describe the flow structure of ridges and local features that describe the minute details of ridges. The classification of a fingerprint is based on its global pattern of ridges and valleys. A valid feature set for fingerprint classification should be able to capture this global information effectively (Jain *et al.*, 1999). Therefore, it is natural to base the features directly on the fingerprint ridges. There are many different ways to extract and represent ridge information. Orientations fields are a convenient way to summarize the ridge-valley patterns of a fingerprint. Fingerprint ridge orientation estimation, especially for low quality image, is still a challenging problem in automatic fingerprint classification and new creative methods for orientation estimation and correction are expected to be proposed and investigated (Zhu *et al.*, 2006).

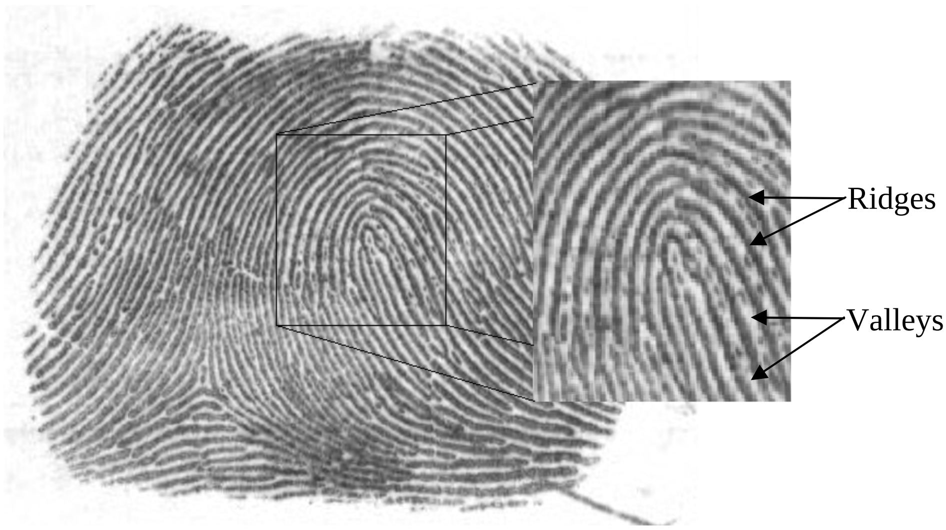


Figure 1.6 Ridges and valleys structure (Right-loop class)

Another feature that is often used for distinguishing fingerprint classes is the existence and location of singular points. The singular points are classified into core and delta as depicted by Figure 1.7. The difficulties faced by singularities-based are: the singular points may not appear in the image, especially if the image is small; the noise in the fingerprint images makes the singular points extraction unreliable, including missing or wrong detection. There are several methods have been proposed to locate the singular points. However, the most common and widely used is the Poincaré index (Li *et al.*, 2007), but this method is very sensitive to noise, low contrast and quality of fingerprint images.

Local averaging of the orientation fields are often quite effective in preventing the detection of false singular points, even if it can lead to slight displacement of the delta position toward the borders (Maltoni *et al.*, 2009). Park *et al.* (2006) proposed the orientation of any two horizontally adjacent elements is checked against a set of pre-defined rules to detect candidate regions of singular points; for each candidate region, its neighboring elements are then analyzed to confirm the presence of singular points. This method is very sensitive to fingerprint image rotation because only the upper and lower cores are used. Wang and Xie

(2004) employ structure shape of orientation fields around the cores when the delta located near the border are failed to be detected.

In relation to that, many techniques have been proposed to locate the singular points; their performances are far from satisfactory, let alone a full automation. Therefore, it is vital to come out with an efficient technique that capable of detecting precisely genuine singular points without to undergo both cropping and realignment pre-processes.

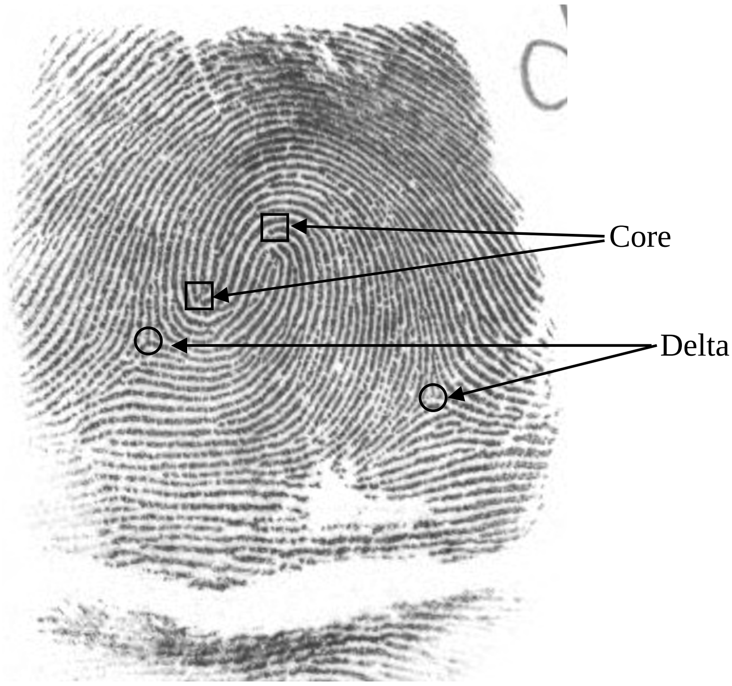


Figure 1.7 Core and delta on a fingerprint image

The above mentioned remaining issues provide a window of research opportunities in this area. In relation to that, the corresponding interrelated research questions that need to be resolved are arranged according to their order of preference:

1. How to automatically segment fingerprint image into background and foreground?
2. How to identify, locate and remove the noises from the foreground?
3. How to accurately estimate the orientation fields?
4. How to precisely detect the genuine singular points?
5. How to accurately classify the fingerprint?

1.3 Problem Statements

Base on the problem background and research questions, the remaining issues can be stated as follows:

1. Generally, fingerprint images of NIST Special Database 14 always vary in terms of shape, size and orientation. Thus, previous studies applied manual cropping to separate foreground from background. Later the foreground is manually realigned and rescaled to obtain appropriate orientation and work area. These non-automatic pre-processes involve human intervention, and therefore should be avoided. Thus, a robust method should be invariant to scaling and rotation.
2. Naturally, many noises exist in fingerprints especially inked prints due excessive or insufficiently used of inks. To accurately identify, locate and remove the noises require a novel approach so that it does not damage the ridges structure and break their flows.
3. Accurate orientation fields are paramount importance prior to singular points detection. Most previous studies employed pre-define angles (for instance, 0, 45, 90, 135, 180 degrees) to represent the ridges' orientations (Ratha *et al.*, 1995; Wang and Xie, 2004; Hsieh *et al.*, 2005; Zhang and Yan, 2007). However, these rigid pre-set angles do not truly reflect the actual ridges orientations. In fact, it resulted in many fake singular points. In addition, to identify and eliminate these artificial singular points are time consuming and tedious and therefore require a special tool to undertake the job.
4. Original Poincaré index is considered a robust technique to locate the singular points and its performance is heavily relied on quality of the orientation fields (Zhang and Yan, 2007; Maltoni *et al.*, 2009). However, most researchers have simplified the index to suite their requirements. Furthermore, most previous studies directly employed the Poincaré index to determine the singular points without first undergo filtering mechanism to short list the potential candidate of genuine singular points. This resulted in many false singular points. Therefore, an efficient algorithm is required to filter the singular points.

5. There is a wide variety of orientation fields-based classification methods that have been proposed by previous researches including geometric-based, structure-based, rule-based, learning-based, statistical-based, and hybrid (Jain *et al.*, 1999; Maltoni *et al.*, 2009). However, most of the techniques are considered rigid and involved human intervention during pre-processing stage. Moreover, most of their experiments were based on unreliable dataset such as NIST database 4 which contains 2000 pre-segmented and pre-cropped prints (Cappelli and Maltoni, 2009). This limited number of pre-processed prints is considered small and unnatural, and therefore, is not reliable to be an appropriate testing platform for the fingerprint classification. In addition, some studies have also employed standard dataset but with unreliable sample size (i.e. insufficient and biased), except for Cappelli and Maltoni (2009). Hence, their experimental results and as well as the proposed methods are disputable.

1.4 Research Goal

To develop an automatic ridges orientation structure-based fingerprint classification method that covers foreground segmentation, noise removal, enhancement, orientation field estimation, singular point detection, and classification.

1.5 Objectives of Study

In order to fulfil the above goal, the following objectives are to be targeted:

1. To propose a new automatic fingerprint classification scheme.
2. To propose a new pre-processing technique that includes image segmentation and enhancement. The technique should be able to segment the fingerprints from its background and discards all foreign objects such

as handwritten annotation and artefacts found in the inked prints. Also, it should be able to improve the foreground image quality.

3. To propose a new orientation field’ estimation approach that utilizes true angle of the orientation fields in accordance to natural gradient of the ridge’s structure of the prints.
4. To propose a new singular point detection technique using a filtering mechanism. This mechanism is functioned to filter singular points in order to minimize of both fake core and delta.
5. To propose a new rule-based classification method using singular points and structure shape of orientation fields.

1.6 Scope of the Study

This thesis involves a complete process of automatic fingerprint classification including fingerprint segmentation, fingerprint enhancement, orientation field estimation, singular point detection, and finally fingerprint classification.

Moreover, as for the standard dataset testing platform, this study employed grey-scale fingerprint images obtained from the NIST Special Database 14. The database is made up of 54,000 8-bit grey-scale images of rolled fingerprint impressions scanned from 27,000 persons using both ink and life scanner. All the prints in the database contain handwritten annotations labelled by human experts during a manual fingerprint classification process. The fingerprints also contain inheritance handicaps or defects such as noise, scars, cuts, bruises, wet, dry and low contrast. Furthermore, to reflect a real life environment, the fingerprints are taken in their natural forms which contain the above handicaps, and also are free of manual cropping and realignment. In addition, since this work is benchmarked with the latest work of Cappelli and Maltoni (2009), the identical sample (i.e. f0000001 to f0027000 prints) is used. Furthermore, for the same reason, scarred prints are excluded from the scope of this study.

1.7 List of Research Contributions

The contributions of this study can be grouped into six findings namely, new scheme of fingerprint classification, segmentation, enhancement, orientation fields estimation, singular points detection, and classification.

- New scheme of fingerprint classification

  A new scheme of fully automatic fingerprint classification system is proposed. This scheme is free of cropping and realignment processes, and can be considered as a significant progress compared to the previous methods. Besides, it also introduced a novel filtering mechanism to filter singular points. The scheme has successfully been tested on de facto standard dataset NIST Special Database 14 using 27000 prints. The experimental results have revealed that the scheme outperformed the most recent Cappelli and Maltoni's work (2009) who are been considered as the most respected researchers in this area.

- Segmentation

  A new segmentation method is proposed using a combined local mean and local variance of gradient magnitudes approach. This technique has successfully extracted the foreground from background of fingerprint image without human intervention.

- Enhancement

  Once the foreground is extracted, enhancement process is followed. For this purpose, a new enhancement technique is proposed. In this approach, the noisy areas are identified, enhanced and labelled, and subsequently the noises are removed. The strong point of this technique is that the focal point of the enhancement is only on the noisy areas, while clean areas of the fingerprint are left unchanged. Therefore, it is not only improved the speed, is also does not encroach on the rest of the clean areas. Once the noise removal is completed, then a 3×3 Gaussian filter is applied on the entire image to further refine the foreground.

- Orientation fields estimation

  A new method to precisely estimate orientation fields is proposed. This method take advantage of true angles of the orientation fields in accordance to natural gradient of ridges structure of the prints. This is considered an edge over the previous studies which use pre-set angles to estimate the orientation fields.

- Singular point detection

  A novel filtering mechanism is proposed using orientation fields structure. This mechanism has successfully indentified and precisely determined potential candidate regions that most likely contain singular points. This novel approach acts like a filter in which candidate regions of singular point are first searched. Then, for each candidate region, the Poincarè index is applied to seek for genuine singular point (i.e. core or delta). This process has significantly reduced number of fake singular points. In fact, in most cases, not even a single false singular point is found.

- Classification

  A novel orientation fields-based classification method is proposed using rule-based approach that utilizes both singular points and orientation fields' structure. This technique is considered non-rigid since it utilized true angles of the orientation fields. Therefore, it is considered robust and invariant to scaling and rotation.

1.8 Significance of the Study

The above remaining issues and shortcomings of the previous works still exist despite numerous efforts to fix the problems. This compels the author to embark a research work to resolve the drawbacks. Although, some studies have claimed that their proposed classification methods have successfully classified fingerprints with a success rate of more than 90%, their results and as well as the proposed methods are disputable because the datasets used are relatively small and insufficient for them to make a judgement. Worse still, most studies engaged both cropping and realignment manually. These non-automatic processes are considered time consuming and tedious and obviously are impractical for a real life application.

Against a backdrop of the above highlighted issues, this research is vital to resolve all the drawbacks including automating all the processes and using de facto standard dataset with sufficient and unbiased sample. Nonetheless, the significance of this study is not only limited to knowledge enrichment, it also can be applied to real life applications, for instance, multipurpose national identity cards, Automated Teller Machine cards, and cross-border-access immigration project.

1.9 Research Framework

This is an experimental-based study as depicted in Figure 1.8 below. It begins with literature reviews to find the remaining issues and shortcomings of the existing methods and also to learn past experiences. Then, it's followed by analysing the fingerprints of the NIST Special Database 14. In this case, minute details of the prints are studied in order to devise a suitable approach that can be applied to solve the problems that associated with the fingerprints' quality. Amongst the many issues are low contrast, wet prints, dry prints, noises, handwritten annotations, and artefacts.

Next, recent segmentation approaches are also studied to find their strengths and weaknesses. Subsequently, a new segmentation technique is introduced to extract the foreground and as well as to discard all unrelated foreign objects such as handwritten annotations and artefacts.

Once an alien-free foreground is extracted from its background through the segmentation process, the noises are then removed by using a novel noise removal technique. Then, orientation fields' estimation of the foreground is performed. Subsequently, a refinement process is done on the orientation fields by focusing on the noises' areas of the foreground. Later, a singular point detection technique is applied to seek for a genuine core and delta. This technique is coupled with a filtering mechanism to filter the singular points.

Subsequently, a classification is performed by examining both the core and delta in terms of their numbers and positions. Concurrently, all orientation fields which are considered as neighbours of the singular point are also analysed with regard to their patterns or shapes. The technique is then evaluated by using the standard error rate performance measure of the fingerprints sample used. Finally, the results are benchmarked with the latest work of Cappelli and Maltoni (2009).

1.10 Thesis Outline

This thesis consists of five chapters namely, Introduction, Literature Review, Methodology, Experimental Results and Discussions, and finally Conclusion. This introduction chapter is followed by the second chapter which discusses about related works by the previous authors. Among the topics reviewed are segmentation, enhancement, orientation field estimation, singular point detection, and classification of fingerprints.

The third chapter proposes a new fully automatic fingerprint classification method including new scheme of fingerprint classification approach, foreground extraction, noise areas detection and removal, orientation fields' enhancement and estimation, singular points' filtering mechanism, singular points detection, and rule-based classification approach.

Fourth chapter begins with introduction, and followed by dataset used, experimental setting, performance evaluations, and discussions of the results of the implementations including segmentation, enhancement, orientation field estimation, singular point detection and classification of fingerprints.

Finally, Conclusion chapter begins with a review of the mentioned remaining issues, objectives and proposed approaches, and ends with highlighting the achievements and suggestions for future works.

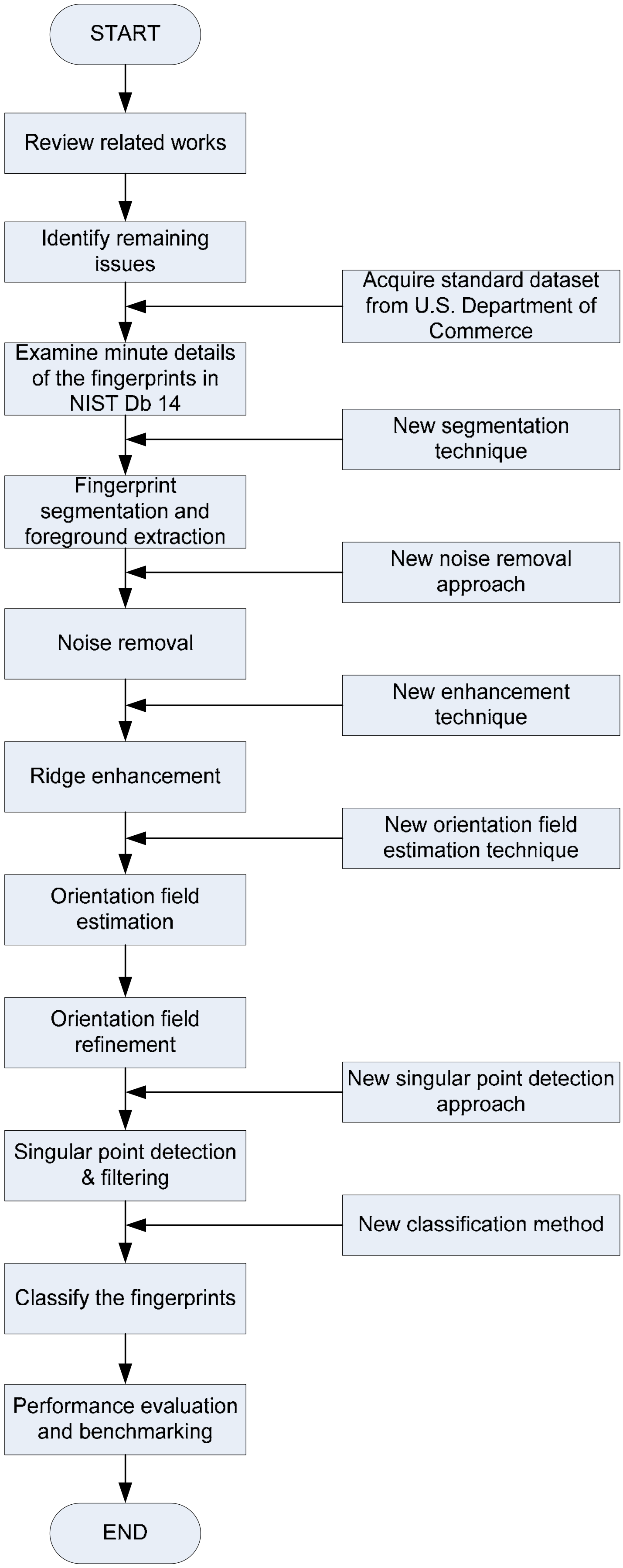


Figure 1.8 Research framework flowcharts

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