EFFICIENT APPROACHES FOR FINGERPRINT AND PALMPRINT RECOGNITION

A THESIS

submitted by

A. TIRUPATHI RAO

for the award of the degree

of

DOCTOR OF PHILOSOPHY

भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY HYDERABAD

JUNE 2016

THESIS CERTIFICATE

This is to certify that the thesis entitled **Efficient Approaches for Fingerprint and Palmprint Recognition** submitted by **A. Tirupathi Rao** to the Indian Institute of Technology Hyderabad for the award of the degree of Doctor of Philosophy is a bonafide record of research work carried out by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

C. Krishna Mohan

Dr. C. Krishna Mohan

Dept. of Computer Science and Engg.

Hyderabad - 502 285

Date: 9/6/2016.

ATRao

CS10P004.

CERTIFICATE

This is to certify that Mr.A.Tirupathi Rao (Roll No: CS10P004) research scholar from CSE department of Indian Institute of Technology Hyderabad has successfully defended viva-voce examination for his PhD thesis entitled "**Efficient Approaches for Fingerprint and Palmprint Recognition**" on 15th Jul 2016.

C. Krishna Mohan

Dr. C. Krishna Mohan

C. Krishna Mohan
Associate Professor
Department of Computer Science and Engineering
Indian Institute of Technology Hyderabad
Kandi-502285, Sangareddy, Telangana, India.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to Dr. C. Krishna Mohan for providing me with the opportunity to do my research work under his guidance. His emphasis on steady and committed effort has motivated me during the course of the research work. I have immensely benefited from the excellent research environment that he has created and nurtured.

I extremely grateful to our director, Prof. U.B. Desai, for providing excellent computing facilities and such a nice atmosphere for doing my research work. I am extremely thankful to my doctoral committee members Dr. Bheemarjuna Reddy Tamma, Dr. K. Sri Rama Murthy, Dr. C. S. Sastry and my doctoral committee chairman Dr. M. V. Pandu Ranga Rao.

I would like to take this opportunity to thank my beloved parents and my wife Sujatha, son Vishnu Vardhan, daughter Tejaswini, father Pulla Rao and grand mother Bagyamma who have been moral boosters to me and who encouraged me to take up this course and supported me with their love and affection. My special thanks to E. Paul, N. Pattabhi Ramaiah, Mettu Srinivas, V. Nageswa Rao and my classmates for their support, motivation and help at critical moments during my project work. I convey my heartfelt thanks to Visual Learning and Intelligence Group (VIGIL) team for their help in completing my work successfully. Finally, I thank everyone who helped me directly or indirectly during my stay at IIT Hyderabad.

I would like to thank my teachers for making me what I am today. I express my heartfelt appreciation and gratitude to CMC Limited, 4G Identity Solutions, BioMoRF Systems Limited, Lonesoft Technologies and Technobrain India Pvt limited for providing me opportunity to continue my PhD. I thank my collegues NNM, Dr. B. M. Mehtre, Ramam, V. Ragavendra Reddy, Rahul Parthe, Kiran Tadakha, Dinesh , G Kiran, Ravi, Nandan Gopal Krishna, Vaka Srinivasa Reddy, Ch. Chandra Shekar, A.

V. Naresh, Akhil Jain, Vishnu Vardhan, Rama Krishna and Linga Murhty.

My sincere thanks to all my relatives. I am thankful to all those who have directly or indirectly provided me with guidance, moral support or any other kind of help.

Needless to mention is the love, affection, moral support and sacrifice of all my family members, without which this work would not have been possible.

A. Tirupathi Rao

ABSTRACT

Keywords: *fingerprint; palmprint; latent fingerprints; minutiae; triplets; quadruplets; minutiae cylinder codes; optical sensors; binarization; thinning; ridges; valleys; thenar; cross-sensor; nearest neighbour; identification; verification*

Fingerprint and palmprint are the commonly used biometric traits among all the biometrics. With the drastic improvement in technology, biometrics are making their way to mobile handheld devices, with limited storage and computation power. So, there is a need for recognition approaches that are efficient and optimal in resource utilization. In this thesis, we propose techniques to improve the overall efficiency and response time of fingerprint and palmprint recognition systems. To achieve this, we propose various approaches targeting the different stages in a biometric recognition system, namely, pre-processing, feature extraction, and matching. In this thesis, the following methods are proposed: 1) enhancements in pre-processing stage to improve the efficiency of extracting the minutiae points that increases the performance of cross sensors fingerprint matching, 2) efficient fingerprint matching using hybrid fingerprint matching with k-nearest neighbors and minutia quadruplet features, 3) semi-automated latent fingerprint recognition using global minutia matching technique, and 4) efficient minutiae point detection in feature extraction for palmprint recognition, and efficient minutiae quadruplet matching to improve the accuracy of high resolution full palmprint matching.

The first approach in this thesis aims to improve the accuracy of minutia detection using local and global adaptive binarization in pre-processing stage. The performance of fingerprint sensors deteriorate over time which causes the appearance of noise and ghost images in the background during capture which in turn produces too many false minutiae points in feature extraction. To remove these false minutiae, we propose a

local and global adaptive binarization that reduces the noise and ghost images present in the fingerprint background. A comparative study is conducted to evaluate the proposed technique across 3 optical sensors, namely, Cogent-200, BioMini-Plus, and Upek, in the presence of ghosting and noise. We demonstrate that removal of false minutiae using local and global adaptive binarization improves, the performance of global minutiae matching and NIST Bozorth matching algorithms.

The existing fingerprint matching algorithms use more information in memory, due to which the matching process is time consuming. So, we propose a hybrid matching algorithm with k-nearest neighbor and minutia quadruplets for recognising plain fingerprint. The minutiae quadruplets are calculated considering very few characteristics of minutiae points to reduce the memory required for storage and subsequently the time required for matching. The space and time complexity of proposed approach are evaluated on the finger vendor competition (FVC) ongoing data set with ISO/IEC 19794-2 template matching and verified against other existing minutiae based matching algorithms. We further compare the recognition accuracy of the proposed approach with triplet based matching on the FVC 2004 and FVC ongoing data sets. Experimental studies suggest that our approach achieves comparable performance while using less memory and computation time.

In forensic applications, the latent fingerprints are of poor quality and are partial prints(i.e. minimal common area between two captured prints), there by making recognition and matching a challenging task. Therefore, a fingerprint expert needs to accurately mark the minutiae points on latent prints before they can be used for identification. So, in the third approach, we present a semi-automated latent fingerprint recognition algorithm using global minutiae matching technique on the standard ISO/IEC 19794-2 templates. We demonstrate the efficacy of the proposed method on the standard NIST SD-27 fingerprint database.

Palmprint recognition closely resembles fingerprint matching as the matching criteria and minutiae feature extraction methods are almost similar. As 30% of latent prints are palm prints, there is a need for high performance palmprint matching al-

gorithms. Also, in regions of palmprint with high distortion, extraction of genuine minutia points is a challenge. So, we propose an efficient palmprint feature extraction and matching algorithm using nearest neighbour minutiae quadruplets, which improves the efficiency of matching by discarding false minutia points in the identification of probable matching minutiae candidates. Further, our algorithm is a full palm to full palm matching technique, which reduces the chance of missing common areas, unlike existing palmprint matching techniques that are based on segmentation. We show that the proposed method achieves better equal error rates on the FVC ongoing and THUPALMLAB data sets.

Finally, we demonstrate the feasibility of using our approaches for a large-scale fingerprint authentication by evaluating them for public distribution system (PDS) using point-of-sale (PoS) devices. In the traditional PDS systems, the commodities distribution is paper based, which lacks transparency and can be easily tampered (misused). So, we propose a system that uses fingerprint based authentication to distribute the commodities. A PoS device captures a persons fingerprint and authenticates with reference fingerprints from the Aadhaar central information repository. In the proposed system, genuine beneficiaries can be identified more accurately and misuse of government subsidies can be avoided.

In summary, this thesis proposes various approaches to improve fingerprint recognition by introducing adaptive binarization for efficient minutia extraction. A hybrid fingerprint matching algorithm using minutiae quadruplets and k-nearest neighbor is proposed that uses less space and time for plain fingerprint recognition. A semi-automated matching on latent fingerprint is also proposed using global minutiae matching. This thesis also proposes to use minutiae quadruplets for full palm to palm matching, there by eliminating the need for segmentation. We also demonstrate that the methods developed during the course of this thesis can be used for large-scale e-governance applications.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

FAR	- False Accept Rate
FRR	- False Reject Rate
EER	- Equal Error Rate
FER	- Failure to Enroll Rate
DET	- Detection Error Trade-off
FMR	- False match Rate
FNMR	- False Non-match Rate
AFIS	- Automated Fingerprint Identification System
APIS	- Automated Palmprint Identification System
ROC	- Receiver Operating Characteristic
ED	- Euclidean Distance
JPEG	- Joint Photographic Experts Group
JP2	- JPEG 2000
ISO	- International Organization for Standardization
NIST	- National Institute of Standards and Technology
NFIQ	- NIST Fingerprint Image Quality
WSQ	- Wavelet Scalar Quantization
UIDAI	- Unique Identity Authority of India
GMM	- Global Minutiae Matching
NN	- Nearest Neighbors
NNMQ	- Nearest Neighbor Minutiae Quadruplets
LFS	- Latent Fingerprint System
FVC	- Finger Vendor Comptetion
POS	- Point Of Sale
PDS	- Public Distribution System
GPRS	- General Packet Radio Service
GSM	- Global System for Mobile communications

CHAPTER 1

INTRODUCTION TO FINGERPRINTS AND PALMPRINTS

Biometrics is the process of recognizing an individual on physiological or behavioral traits in real-time. Biometrics of an individual are unique and consistent. Biometrics offer an alternative to conventional authentication approaches that cannot be forgotten or lost. A broad range of biometrics like fingerprint, palmprint, iris, signature and voice (Fig 1.1) are used in real-time applications. The increase in the volume of transactions on handheld devices and the number of clients to be identified, are the motivation for designing efficient real-time fingerprint and palmprint recognition algorithm using less memory. Similarly, automatic latent fingerprint recognition is still a challenging problem due to it's partial image and noisy nature. In Section 1.1, fingerprints and the challenges associated with the use of different fingerprint sensors are described. Section 1.2, discusses palmprints and the performance of various biometrics. In Section 1.3, we briefly describe various applications of fingerprints. Section 1.4 outlines some of the issues related to fingerprint and palmprint recognition. Section 1.5 outlines the organization of this thesis.

Among these biometrics, fingerprint and palmprint based identification are the most widely used techniques. The typical block diagram of biometric recognition system is shown in figure 1.2. The block diagram shows the various phases involved in a biometric recognition system. Here, the sensors used to capture the biometric trait use different sensing technologies such as optical, and capacitive. The captured biometrics is passed to the pre-processing to enhance the image quality and then passed to extract the feature using template generator. The template received from template generator is matched against the stored templates in the matching stage to produce

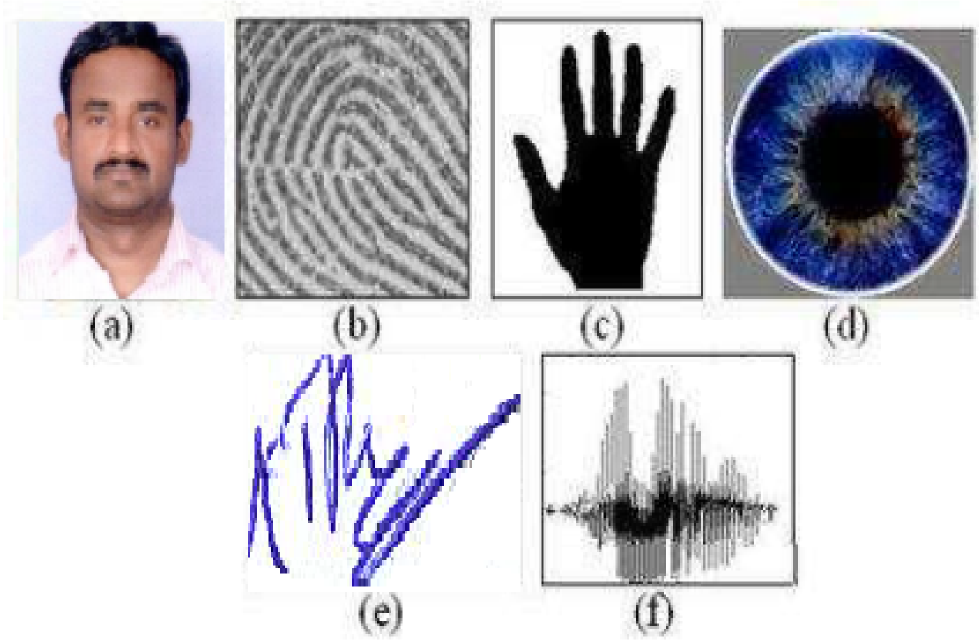


Fig. 1.1: Types of biometrics: Physiological (a) face (b) fingerprint (c) palm (d) iris. Behavioral (e) signature (f) voice.

the matching result.

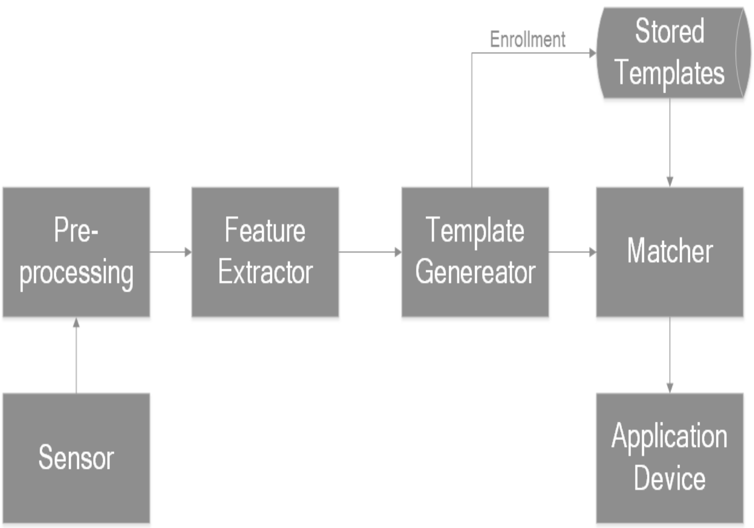


Fig. 1.2: Typical block diagram of biometric recognition system.

1.1 INTRODUCTION TO FINGERPRINTS

A fingerprint is an impression left by the friction ridges of a finger. A ridge is a curved line in a finger print. Among the patterns in a fingerprint, shown in fig 1.3, the minutiae points (ridge bifurcation and ridge ending) are unique and are not genetically inherited. In addition to humans, monkeys and apes also have friction ridge skin (FRS) covering their hands. A friction ridge skin consists of a series of furrows and ridges that is unique and consistent through out the life span. This friction ridges provides friction for grasping things. A fingerprint generally refers to the pattern of friction ridge skin on finger tips.

The pattern formed by fingerprints can be classified into one of the three major categories: a whorl, loop (left loop and right loop) and arch. A whorl is a pattern with single core and two delta's. A core is the inner most re-curve of a fingerprint and delta is the shape formed by ridges that flow in three directions as shown in figure 1.3. A fingerprint with one core and one delta is a loop and depending on whether the delta lies on the left or right side of the core, it is refereed as left or right loop. In the 10 fingerprints of a person, one may have some or all of these patterns. These patterns are not sufficient to uniquely recognise a person, due to which the next level features like minutiae points need to be considered. Other features like creases, incipient ridges, and the shapes of the ridge edges can also be used to recognize a person.

Early pioneers in the field of friction ridge skin (FRS) pattern study have demonstrated that the overall size, pattern, spacing, and shape of the ridges are genetically inherited. The ridge features (minutiae points, ridge shape, ridge directions) that are used for recognition are not inheritable which makes fingerprints unique.

A fingerprint-based biometric system is essentially a pattern recognition system that recognizes a person by determining the authenticity of his/her fingerprint. Depending on the context (i.e. 1:1 or 1:n matching), a fingerprint-based biometric system may be considered as a verification system or an identification system:

1. A verification system authenticates a person's identity by comparing the cap-

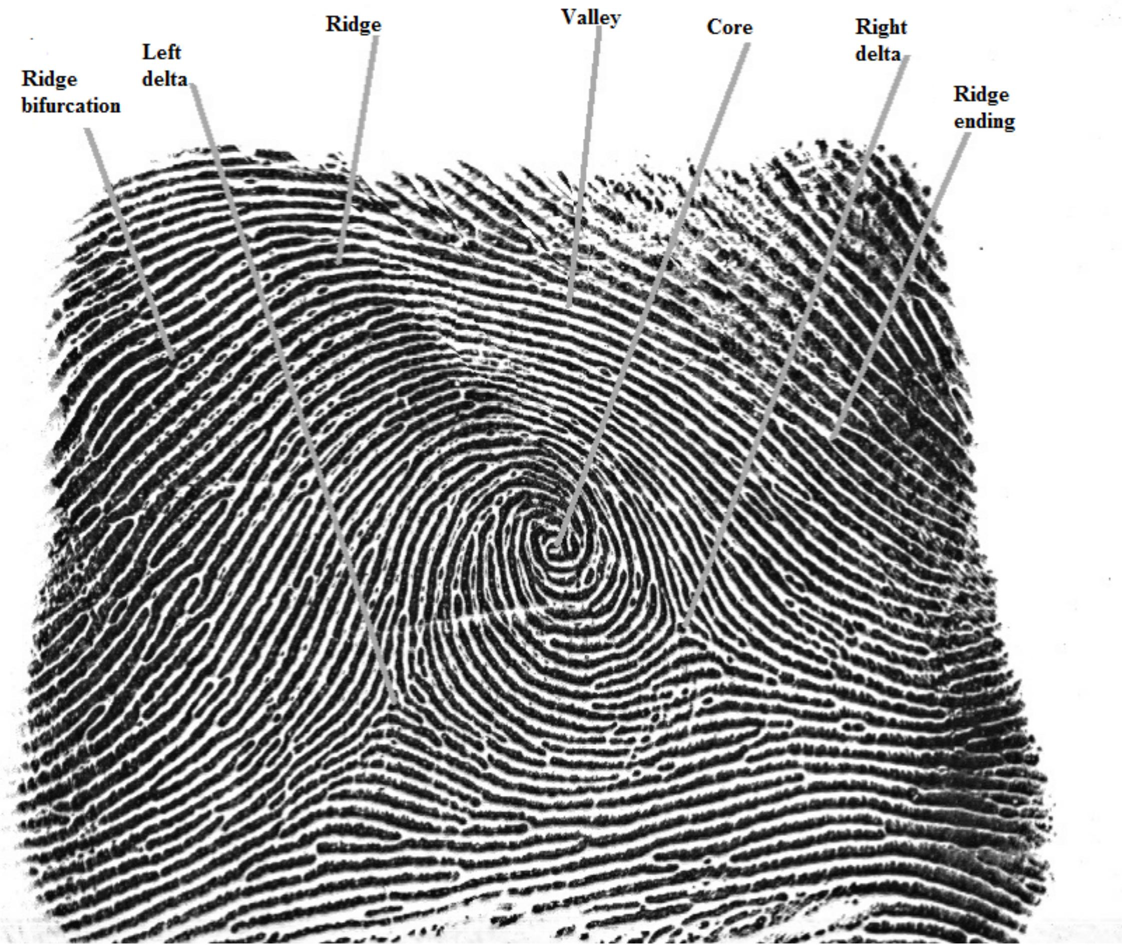


Fig. 1.3: Fingerprint features

tured fingerprints with his/her own biometric template(s) pre-stored in the system. Verification compares one-to-one to determine if the claimed identity of the individual is true. This is same as the person asking the biometric system "Am I who I claim to be? ".

2. An identification system recognizes an individual by searching the entire template database for a match. It conducts one-to-many comparison to establish the identity of the individual. This is more like asking the biometric system "Who am I? ".

Throughout this thesis, recognition is used when there is no need to distinguish between identification and verification. The block diagram for enrollment, verification and identification is shown in fig 1.4. The registration of an individual into biometric system will be taken care by the enrollment module. During enrollment, finger impression from scanner is used to create a raw digital finger representation. The quality checking ensures that the obtained fingerprint can be used by progressive stages. The fingerprint is generally processed by a feature extractor to produce a compact discriminative representation called a template. During verification, the fingerprint scanner scans the digital fingerprint of an individual, which is processed by the feature extractor to generate a template. The resulting template is passed to the fingerprint matcher, which compares the templates of the user, the person claims to be.

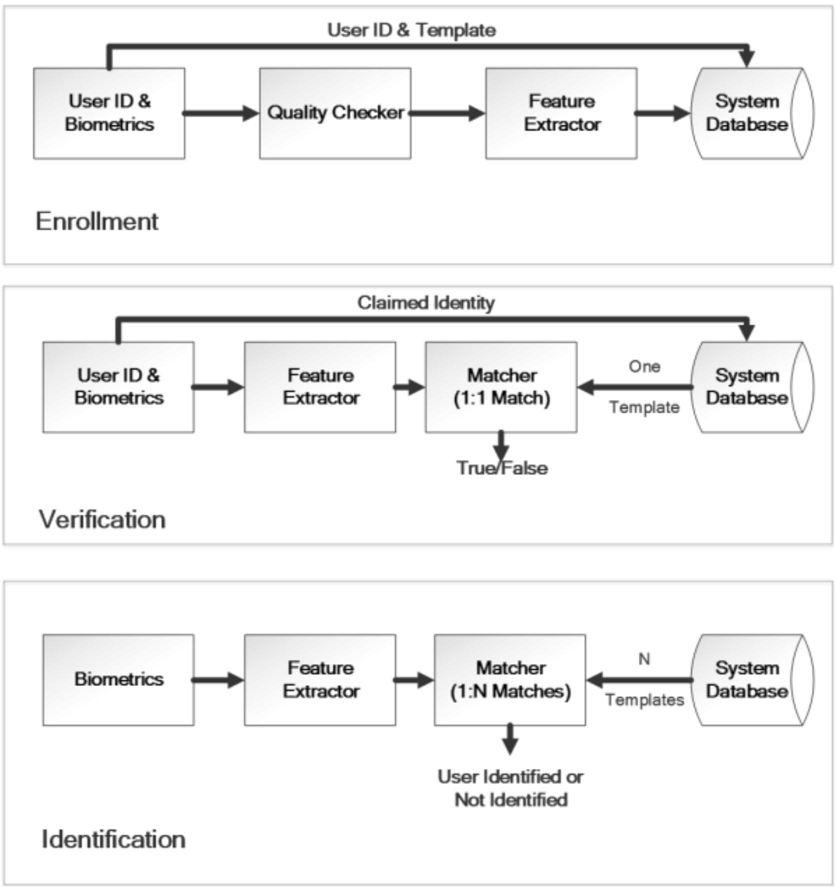


Fig. 1.4: Typical block diagram for enrollment, verification and identification

Fingerprints are the patterns formed by ridges and furrows present on the finger tip [1] that are extensively used for personal identification [2]. Figure 1.3 depicts a sample finger impression with the location of various features captured from live scanner at 500dpi. Approximately 4% of the population do not have good quality fingerprints which can not be appropriately captured with the fingerprint sensors. The reasons include scratches incurred during heavy labor, peeling of skin due to climatic conditions, perpetual wrinkles due to age, interim wrinkles caused by extended inundation in water, and filthy fingers. Further, fingerprints can not be captured without the person's cooperation, due to this fingerprints are not suited for applications like surveillance.

1.1.1 Issues in fingerprint recognition

Some of the unresolved issues in automatic fingerprint identification are: There are so many sensors are there to capture the fingerprint. The authentication sensors capturing area is small in size causes in capturing of small finger area. The different sensing technologies have been discussed as below:

1. The new generation solid-state sensors are being increasingly used to acquire fingerprint images. These sensors when embedded in compact systems like laptops, mouse, and cellular phones provide a small contact area (e.g., $0.6inch \times 0.6inch$ in Upek, Suprema BioMini sensors) for the fingertip, and therefore sense only a limited portion of the fingerprint. This complicates the problem of recognizing impressions due to the lack of required minutiae points. It is therefore essential to augment minutiae points with other information available with fingerprints, to deal with this partial fingerprints.

2. Due to advancements in sensor technology, a variety of fingerprint sensors with different specifications are now available (Figure 1.5). However, a fingerprint matching system developed for a particular sensor is very often not compatible with images acquired using other sensors. This lack of interoperability limits the utility of

a matcher.

Fig. 1.5: Different types of sensors

3. The fingerprint matching performance is affected by the non-linear distortions present in the fingerprint image. These distortions are a consequence of the imaging process which requires the finger to be pressed against the sensor surface. To facilitate good matching performance, these distortions have to be accounted for prior to the matching stage.

4. While it is acknowledged that the fingerprints of a person do not change over time, it is possible for minor cuts and bruises to alter the ridge structure of fingerprints. Moreover, the moisture content of the fingertip may change over time affecting the quality of the fingerprint image being acquired from a user. The template fingerprint data obtained during enrollment time may not capture these variations. A protocol to update template data is necessary to maintain the performance of the system.

5. Some users consistently provide poor quality fingerprints due to the dry nature of their skin. It is difficult to extract features from such poor quality images. Users

providing such noisy fingerprint data might find it difficult to enroll in and interact with a biometric system that uses only fingerprints. To address the issues, there is a need to consider a multi-biometric system that uses biometric traits along with fingerprints.

1.2 INTRODUCTION TO PALMPRINTS

Palm refers to the inward part of a person's hand. Palmprint is additionally one of the solid modalities since it has a larger number of features than that of alternate modalities, like iris, face etc. Palm has characteristics like principal lines, minutiae points, ridges and creases as shown in figure 1.6 [3]. The principal lines are: 1) heart line, 2) head line, and 3) life line [4] [5]. These three key lines separate palm into three parts interdigital, hypothenar, and thenar. An *interdigital* locale lies over the heart line. The *thenar* lies beneath the life line and *hypothenar* is in the middle of heart and life line.

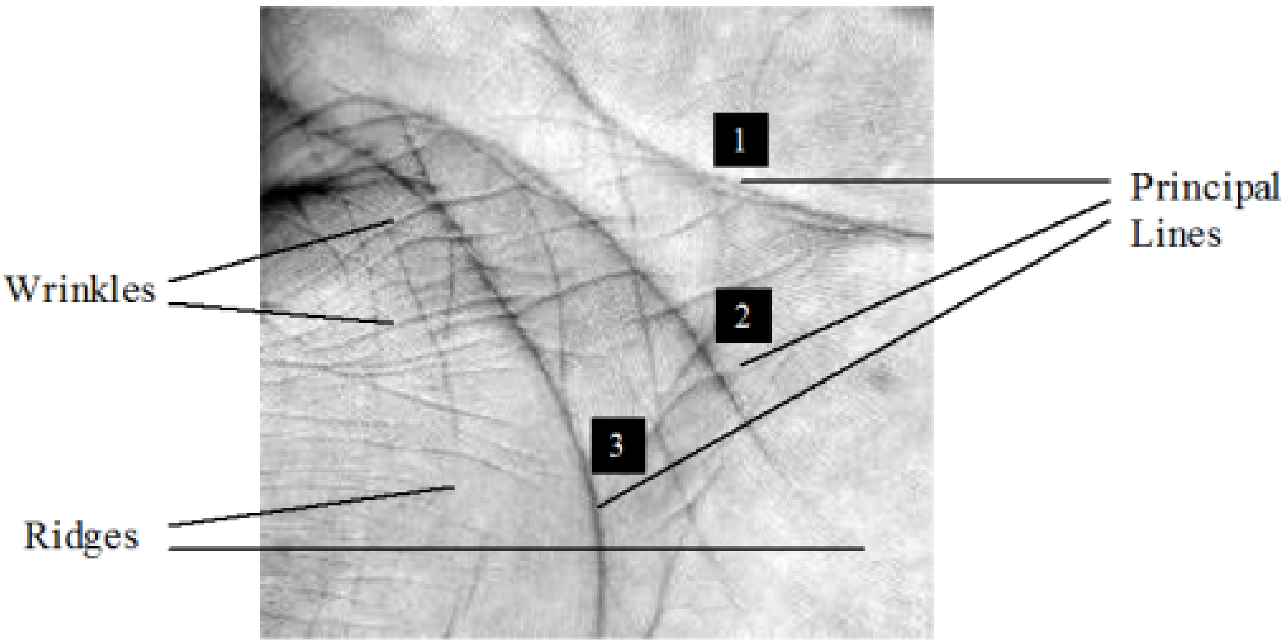


Fig. 1.6: Palmprint features ([3])

1.2.1 Issues in palmprint recognition

Palmprints share the some of the common features that fingerprints have like, ridges, valleys, and minutiae points. The typical palmprint will be twenty times bigger than the size of the fingerprint captured at 500ppi. Due to this the palmprint recognition is a challenging problem with images capture at high resolution. The time taken on high resolution palmprint recognition is 100 to 120 times slow. So, there is need for fast and accurate algorithms for palmprint recognition.

1.2.2 Performance of biometric based recognition system

There are two types of errors in biometric recognition system, namely, false acceptance rate (FAR) and false rejection rate (FRR). The false acceptance rate is accepting the impostor as genuine. The false rejection rate is rejecting the genuine as impostor. The errors false acceptance and false rejection are also called false match/false non-match in a understandable way. There needs a strict trade off between false non-match rate (FNMR) and false match rate (FMR) in every biometric system. In fact, both false non-match rate and false match rate are functions of a biometric system accuracy with the threshold T. If T is decreased to make the system more tolerant to input variations and noise, then FMR increases, and if the threshold T is increased to make the system secure, then false non-match rate also increases. The equal error rate (EER) i.e the error rate at the threshold where FNMR and FMR coincides is used to summarise the biometric recognition system accuracy, besides FRR and FAR. Figure 1.7 shows the ROC curve for biometrics systems. The smaller the EER, the more robust the biometric system.

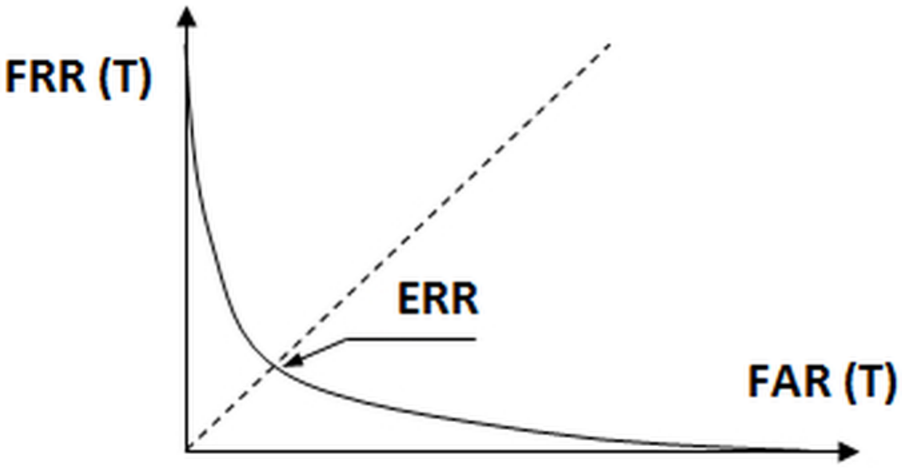


Fig. 1.7: ROC curve to measure the performance of a biometric system.

1.3 APPLICATIONS OF BIOMETRICS

Token-based authentication is traditionally used in the physical access control applications. With the progress and affordability of fingerprint technology, these applications are adopting fingerprint authentication. Biometrics are also used in various criminal and civilian applications like a) latent (partial) fingerprints collected from crime scene are used in forensic application to identify the suspects, b) national identity like Aadhar [6] has incorporated fingerprints and iris biometrics to identify its citizen's, and c) civilian applications like e-commerce, access control, remote login and data access applications are using biometrics for authentication. There is a rapid increase in the number transactions related to electronic banking, electronic commerce and electronic transactions. These applications are becoming most important emerging applications of biometrics, as the fingerprint sensors are at reachable price.

1.4 ISSUES ADDRESSED IN THIS THESIS

Even though the fingerprint recognition system is more advanced and automated, it still suffers with few shortcomings when it is applied in real-time identification scenarios, for example, the factors like the enrollment time, identification time, fingerprint sensor variations, and memory required for storing the fingerprint features, will make lot of impact on the identification rate. In this thesis, these issues are addressed using three different types of fingerprint images, namely, plain fingerprints, latent fingerprints and palmprints.

- The fingerprint sensors captures the fingerprints with ghost images and noise as background. These noisy fingerprints generate lot of spurious minutiae in the feature extraction, which reduces the accuracy of fingerprint recognition. So, there is need to process the image at the pre-processing stage to remove the noise, and ghost images.
- The existing fingerprint minutiae algorithms holds lot of information for matching two fingerprints. Due, to this the existing algorithms are very slow and consumes more memory while matching. So, there is a need for developing algorithms that hold few characteristics of minutiae points to reduce space and time complexities.
- The latent prints are very poor quality fingerprint images. The automatic extraction of minutiae points from latent fingerprints is very challenging. To process latent print fingerprint experts need to mark the minutiae manually to recognise. So, there is a need for algorithms that can work with false minutiae.
- Palmprint recognition is a variant of fingerprint matching as both the systems share almost similar matching criteria and the minutiae feature extraction methods. The performance degradation with palmprint biometrics is because of the failure of extracting genuine minutia points from the region of highly distorted ridge information with huge data. So, there is need for developing the algorithms to handle false minutiae in the palmprints.

1.5 ORGANIZATION OF THE THESIS

An overview of the existing approaches in fingerprint and palmprint recognition systems is presented in Chapter 2. Some of the research issues are identified in chapter 3, where the performance of different optical fingerprint sensors used for authentication are evaluated using open source NIST bozorth and global minutiae matching fingerprint algorithms. In chapter 4, an hybrid fingerprint matching technique using nearest neighbor minutiae and minutiae quadruplets is proposed for plain fingerprint matching. The proposed algorithm is designed to reduce the space and time complexities over fingerprint standard data sets without compromising on accuracy. In chapter 5, a semi-automated latent fingerprint identification approach is proposed that enhances the latent fingerprint during feature extraction and uses a global minutiae matching technique during matching to find the matching short lists for latent fingerprint matching. A new approach using minutiae quadruplets for palmprint recognition which performs full palm to full palm matching is proposed in chapter 6. A large scale real time PDS application using Aadhaar authentication is elaborated in chapter 7. The proposed system uses point of sale (PoS) device with fingerprint scanner, GPRS and thermal printer modules with a back end infrastructure supported by India's Aadhaar. Chapter 8 summarizes the research work carried out as part of this thesis, highlights the contributions of the work and discusses directions for future work.

CHAPTER 2

OVERVIEW OF APPROACHES FOR FINGERPRINT AND PALMPRINT RECOGNITION SYSTEMS

Most of the automatic fingerprint recognition systems use minutiae points for comparison of fingerprints. Minutiae points are local patterns in the fingerprint that correspond to the bifurcations and terminations of the fingerprint ridge lines. Fingerprint classification schemes rely on the global characteristics of fingerprints like core and delta points, with out considering the characteristics of the class being recognized. Even though, the automatic minutiae extraction problem has been extensively studied, it is not yet completely solved. Due to the nature of the acquisition process, the fingerprint quality is often very low and fingerprint images are usually affected by two types of degradation:

1. The ridge lines sometimes include small breaks (gaps) and hence may not be strictly continuous.
2. The presence of cluttering(disordered) noise in ridge lines will not always be well separated.

A great amount of work has been carried out in last few decades to enhance feature extraction(minutiae) from fingerprints. Since the minutiae extracted from feature extraction algorithms are labeled as bifurcations or terminations, three types of error may occur: 1) non-existent minutiae (false), 2) undetected minutiae (dropped), and 3) type exchanged minutiae (exchanged) [7]. Several fingerprint applications, such as e-voting, access control, e-commerce etc. require very low cost acquisition sensors which usually provide images at low resolutions. This chapter reviews some of the existing approaches to fingerprint and palmprint recognition. In Section 2.1, fingerprints and various phases involved in fingerprint recognition are explained in brief. The existing approaches to fingerprint recognition are reviewed in Section 2.2. In Section 2.3, the palmprints and early history is presented. The existing approaches for palmprint recognition system is reviewed in section 2.4. Some research issues arising out of the review of existing methods are identified, which are addressed in this thesis.

2.1 FINGERPRINTS

Fingerprints are the tips of the human hand consists of friction ridges. The fingerprints are the patterns formed by parallel ridges and valleys. The human fingerprints are detailed, nearly unique, difficult to alter, and durable over the life of an individual, making them suitable as long-term markers of human identity.

2.1.1 Suitability of fingerprint as a biometric

The following criteria is used to evaluate the suitability of fingerprint recognition as a biometric solution:

Universality : Most of the fingerprint recognition systems allow multiple fingers for enrollment which ensures that an individual can be granted access even after injury. Only rare case is that a person misses all 10 fingers.

Uniqueness : General acceptance is that fingerprints are distinct to an individual. However, there is a risk of matching fingerprints of two different individuals when the fingerprint image is of low quality. The false acceptance rate (FAR) is mainly dependent on the quality of the fingerprint.

Permanence : Though fingerprints do not change with ageing, they lose collagen as people age, which makes their fingerprint harder to read and this might significantly lead to more false rejects with elderly people. Injuries, such as fire wounds, can damage a fingerprint but if multiple fingers are enrolled then access can easily be granted for the authorized individual.

Ease of Collection : The fingerprints are easy to capture and the cheapest fingerprint readers available use the digital camera to capture the fingerprints. In few environments, where people are not able to clean their hands, there is a need for a more expensive means to capture a usable fingerprint image.

Acceptability : The fingerprints are very well accepted by the individuals and are the most widely used since from decades.

Circumvention : There are various concerns when utilizing fingerprint matching system. The unique finger impression shams are not very hard to make, the exertion is exceptionally reliant of the biometric gadget to be tricked. A percentage of the least expensive gadgets can even be fooled by a fingerprint image that is imprinted on paper or straight forwardness. Shams can be made for every sort of sensor, however, the more confounded (and in this way costly) sensors are the more hard to fool. Liveness location do make fingerprint readers significantly more hard to fool.

A thorough analysis must be done before implementing fingerprint recognition system as a means for identification or verification in a high security areas. Using fingerprint readers without live finger detection (LFD) should be avoided.

Performance : The devices actually in the market should cover any need in terms of speed, accuracy and robustness, except for big government and corporations applications where recognition algorithms might become a bottleneck.

2.1.2 Early history of fingerprint biometrics

One can collect fingerprints from any of the 10 fingers and despite the small size of scanners, they are proven to be effective in many large scale applications over the years.

The evolution of fingerprints [8] recognition system is given below.

- 1890 - Galton and Henry developed the classification systems for fingerprints.
- 1903 - New York State started using fingerprints for prisoners.
- 1905-1908 - US Army, Navy and Marine Corps started using fingerprints.
- 1963 - Research paper on fingerprint automation is published by Hughes.
- 1969 - Automation of fingerprint identification process is pushed forward by Hughes.
- 1975 - Development of sensors and minutiae extraction technology is funded by FBI.
- 1970s - 1980s - NIST leads development of automatic methods of digitizing inked fingerprints and the effects of image compression on image quality, classification, extraction of minutiae, and matching.
- 1980s - FBIs first operational fingerprint matching algorithm M40 was developed.
- 1982 - Five automated fingerprint identification systems (AFIS) are deployed.
- 1994 -Integrated automated fingerprint identification system (IAFIS) competition is held.
- 1999 - FBI's IAFIS major components become operational.
- 2003 - Fingerprint vendor technology evaluation (FpVTE) initiated to evaluate the accuracy of fingerprint recognition systems.
- 2012 - INTERPOL's automated fingerprint identification system repository exceeds 150,000 sets fingerprints for important international criminal records from

190 members.

- 2013 - Apple includes fingerprint scanners into apple smart phones.

2.1.3 Fingerprint recognition system

The automated method of verifying the identity of an individual by comparing two fingerprints is referred to as fingerprint recognition. The fingerprint recognition system is one of the commonly used biometrics, and is by far the most widely used biometric solution for authentication on computerized systems. The reasons for the popularity of fingerprint recognition system are: 1) the ease of acquisition, 2) established use and its acceptance when compared to other biometrics, and 3) the availability of multiple(10) sources of biometric on each individual.

2.1.4 Basic patterns

There are three basic patterns of fingerprint ridges, namely, arch, loop, and whorl as shown in figure 2.1 [9]. An arch is a pattern where the ridge enters one side of the finger, then rises in the center forming an arch, and exits on the other side of the finger. In a loop, the ridge enters on one side of the finger, then forms a curve, and exits on the same side of the finger from which it entered. Loops are the most common patterns in fingerprints. Finally, a whorl is the pattern formed when ridges circle around a central point.

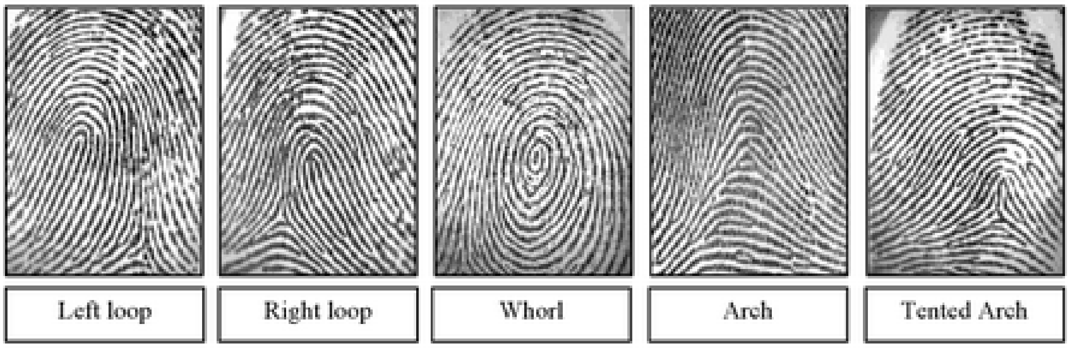


Fig. 2.1: Pattern classes of fingerprints ([9])

2.1.5 Minutiae features

The small details in a fingerprint that are most important for fingerprint recognition are termed as minutiae, which refers to the specific point in a fingerprint. The minutiae features are classified into three major types: 1) the ridge ending, 2) the bifurcation, and 3) the dot (also called short ridge). The ridge ending is the point where a ridge ends. A bifurcation is the point where a ridge splits into two ridges. Spots are those fingerprint ridges that are significantly shorter than other ridges.

2.1.6 Fingerprint readers

The hardware required for reading fingerprints is of four types:

1. *Optical readers* are the most widely recognized sort of unique finger impression readers. The sort of sensor utilized as a part of an optical reader is an advanced camera that obtains a visual picture of the fingerprint. Despite the fact that the optical readers begin at exceptionally modest costs, the readings are affected by filthy or stamped fingers, and this kind of fingerprint readers is easier to fool than others readers.

2. *Capacitive readers(CMOS readers)* do not read the fingerprint utilizing light.

The CMOS readers utilize the capacitor and electrical current to shape an image of the unique finger impression. The CMOS readers are more expensive than optical readers. An essential point of preference of CMOS readers over optical readers is that the CMOS readers require a genuine fingerprint shape as opposed to just a visual image. This makes CMOS readers harder to fool.

3. *Ultrasound readers* are the latest sort of unique finger impression readers as they utilize high frequency sound waves to enter the epidermal (external) layer of the skin and read the unique finger impression on the dermal skin layer, which takes out the requirement for a clean, unscarred surface. For capturing fingerprints that are suitable for biometric authentication, the fingers need to be cleaned before they are placed on the biometric sensor. This sort of fingerprint reader is much more expensive than the initial two, however, because of their precision and the way they are hard to spoof, the ultrasound readers are now extremely prominent.

4. *Thermal readers* sense the difference of temperature on a contact surface between fingerprint ridges and valleys. These fingerprint readers have a number of disadvantages such as higher power consumption and the performance that depends on the environment temperature.

As the sensing region of biometric sensor used to capture the fingerprint is small, the size of the image captured is small and the region of the finger covered changes across recordings. To overcome this issue with the absence of common area across fingerprints, there is a need for robust matching algorithms suitable for small fingerprints.

2.1.7 Fingerprint images

The parameters that characterize a fingerprint digital images are as follows [9].

1. *Resolution*: Resolution indicates the number of dots or pixels per inch (dpi). 250 to 300 dpi is probably the minimum resolution that allows the extraction algorithms to locate the minutiae in fingerprint patterns and 500 dpi is the minimum resolution for federal bureau of investigation (FBI) compliant scanners and is met by many commercial devices.

2. *Area*: The essential parameter is the extent of the rectangular range detected by a fingerprint scanner. The more edges and valleys are caught, and the unique finger impression turns out to be more unmistakable when the area is huge. An area more than or equivalent to 1×1 square inches(as required by FBI determinations) allows a full plain unique finger impression to be gained.

3. *Number of pixels*: The quantity of pixels in a fingerprint can be essentially determined by the fingerprint area and resolution: a scanner working at r dpi over a area of $height(h) \times width(w)$ inches has $rh \times rw$ pixels.

4. *Dynamic range (or depth)*: This signifies the number of bits used to encode the intensity of every pixel. The FBI standard for pixel bit depth is 8 bits, which yields 256 gray levels.

5. *Geometric accuracy*: The maximum geometric distortion introduced by the acquisition device, and expressed as a percentage with respect to x and y directions specifies the geometric accuracy.

6. *Image quality*: The precise way of defining the quality of a fingerprint image is not easy, and to decouple the fingerprint image quality from the intrinsic finger quality or status is even more difficult. In fact, most of the fingerprint device sensors produce low quality images when the ridge appearance is very low (especially for elderly people and manual workers) and when the fingers are too dry, too moist or when they are not properly placed.

2.2 FINGERPRINT RECOGNITION

When a finger is placed with certain pressure against a smooth surface, a fingerprint is produced which is the reproduction of the fingertip epidermis. Interleaved ridges and valleys in a fingerprint image is the most evident structural characteristic pattern of a fingerprint. The ridges (also called ridge lines) are dark whereas valleys are bright. The ridges and valleys often run in parallel; sometimes they bifurcate and sometimes they terminate.

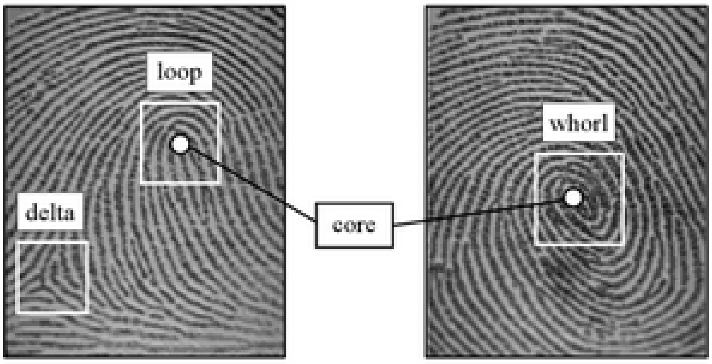


Fig. 2.2: Fingerprint global features ([9])

When analyzed at the global level, one or more regions where the ridge lines assume distinctive shapes (characterized by high curvature, frequent termination, etc.) are exhibited by the fingerprint pattern. These regions (called singularities or singular regions) may be classified into three typologies: delta, loop, and whorl (see Figure 2.2 [9]). The fingerprint images are prealign according to a center point, called the core in many fingerprint recognition algorithms. The core point is the innermost re-curve of the fingerprint. The fingerprints of pattern arch do not contain singularities like delta or core as shown in figure 2.1. In arch pattern, the core is the point of maximum ridge line curvature. Unfortunately, it is difficult to reliably locate a registration (core) point in all the fingerprint images, due to the high variability of fingerprint patterns. Singular regions are commonly used for fingerprint classification [10] (see Figure 2.1), that is, assigning a fingerprint to a class among the set of distinct classes with the aim of simplifying search and retrieval.

The second level features in the fingerprint are minutiae points. The minutiae points are ridge discontinuities. A ridge that ends is end minutiae, and the ridge where it bifurcates into two direction is bifurcation minutiae. There are many more minutiae which are based on ridge discontinuities. The federal bureau of investigation (FBI) mainly considers the two minutiae points called end minutiae and bifurcation minutiae. Each minutiae point will be having the values x, y coordinates, direction in horizontal axis, type of minutiae, and quality.

2.2.1 Local ridge orientation and frequency

The local ridge orientation at $[x, y]$ is the angle θ_{xy} that the fingerprint ridges crossing through an arbitrary small neighborhood centered at $[x, y]$, with respect to the horizontal axis. Based on the computation of gradient phase angles, the local ridge orientation will be extracted. Even though this method is efficient and simple, it has few drawbacks. First, components of the gradient is determined using the classical convolution masks $\bigtriangledown x$ and $\bigtriangledown y$, and computing θ_{ij} as the arctangent of the $\bigtriangledown y / \bigtriangledown x$ ratio, presents problems due to the non-linearity and discontinuity around 90 degrees. Second, a single orientation estimate reflects that the ridgevalley orientation is generally very sensitive to the noise in the fingerprint image. Robust computation, based on local averaging of gradient estimates have been proposed by Kass and Witkin [11], Ratha, Chen, and Jain [12], and Bazen and Gerez [13].

2.2.2 Segmentation

Segmentation is the process of extracting the usable fingerprint area from the capture fingerprint image, which avoids minutiae points extraction from the noisy background. The fingerprint images are striated patterns where the isolation of fingerprint area from background using a local or global thresholding technique [14] is very typical. The real discrimination of background and foreground is not evident from the average intensity value, but can be established from the presence of an oriented pattern in the foreground and an isotropic pattern in the background. If the background of the image is lighter and uniform than the fingerprint portion, then the local intensity could be effective in discriminating background from foreground; The noise generated due to the presence of grease and dust on the sensor needs more powerful segmentation algorithms [15] [7] [12].

2.2.3 Enhancement and binarization

The quality of the fingerprint impacts the performance of minutiae feature extraction algorithms, that effects the fingerprint recognition accuracy. In a typical fingerprint, the furrows and ridges flow in parallel directions to one another locally. In such situations, it is very easy to find the minutiae accurately from the fingerprint. In practice, due to sensor noise, skin distortions, incorrect pressure on sensors, and fingers with low quality, there are nearly 10% of fingerprints of low quality. The goal of an enhancement algorithm is to improve the clarity of the ridge structures in the recoverable regions and mark the unrecoverable regions as too noisy for further processing. Usually, the input of the enhancement algorithm is a gray-scale image. The output may either be a gray-scale or a binary image, depending on the algorithm. Definitive results for fingerprint image enhancement are not produced using general-purpose image enhancement techniques. The fingerprint enhancement algorithms are mainly based on contextual filters. Only one filter is used in conventional filtering techniques where as in contextual filtering, the characteristics of the filter will change as per local characteristics. In enhancement of fingerprint image, the content is defined based on local ridge frequency and orientation. The ridges and valleys sinusoidal shape is defined by local frequency and orientation that slowly varies across the fingerprint image. Undesired noise removal and preserving the true ridge and valley structure can be efficiently done by tuning to the local ridge frequency and orientation using an appropriate filter. An effective method based on Gabor filters is proposed by Hong, Wan, and Jain [16]. Gabor filters have both frequency-selective and orientation-selective properties and have optimal joint resolution in both spatial and frequency domains.

2.2.4 Minutiae extraction

Although rather different from one another, conversion of fingerprint gray-scale image into a binary image is required by most of the existing methods. A priory enhancement greatly benefits binarization processes and on the other hand, a binary output is directly produced by some enhancement algorithms, and the produced binary image is passed to thinning stage [17], which further reduces the thickness of ridge line to one pixel. Finally, minutiae can be detected using the crossing number technique on this thinned image. The minutiae extraction approaches are proposed by some authors that work directly on the gray-scale images without binarization and thinning. This choice is motivated by following considerations:

1. Binarization process may result in loss of significant amount of information;
2. Binarization and thinning are time consuming; a large number of spurious minutiae may be introduced while thinning;
3. In the absence of an a priori enhancement step, most of the binarization techniques do not provide satisfactory results when applied to low-quality images [9].

A direct gray-scale minutiae extraction technique is proposed by Maio and Maltoni [7], whose basic idea is to track the ridge lines in the gray-scale image by sailing according to the local orientation of the ridge pattern. The ridge line extraction algorithm attempts to locate, at each step, a local maximum relative to a section orthogonal to the ridge direction. By connecting the consecutive maxima, a polygonal approximation of the ridge line can be obtained.

2.2.5 Fingerprint matching

Fingerprint recognition on good quality with small intra-class difference is not complex, any reasonable algorithm can perform matching. The major challenge is to recognise the very poor quality images that are affected by:

1. Non-linear distortion: Due to the plasticity present in skin the non-linear distorted fingerprint will be captured from successive captures.
2. High displacement and/or rotation: The placement and orientation of finger will cause the different area capture from successive captures. A finger translation of just 2 mm (which is not perceptible to the user) results in a fingerprint translation of about 40 pixels in a fingerprint captured at 500 dpi.
3. Different pressure and skin condition: If ridges of part of the finger being imaged were in uniform contact with the sensor surface, then the ridge structure of a finger would be accurately captured. However, finger pressure, dryness of the skin, skin disease, sweat, dirt, grease, and humidity in the air all confound the situation, resulting in a non-uniform contact.
4. Feature extraction errors: Measurement errors are often introduced since the feature extraction algorithms are imperfect. For example, in low-quality fingerprint images, a large number of spurious minutiae may be introduced by the minutiae extraction process and may not be able to detect all the true minutiae.

Fingerprint matching based on the large number of existing approaches can be coarsely classified into three families:

1. Correlation-based matching: The correlation between corresponding pixels is computed for different alignments by superimposing the two fingerprint images (e.g., various displacements and rotations) [18] [19] [20].
2. Minutiae-based matching: Sets of points are stored in the two-dimensional plane by extracting minutiae from two fingerprints. In minutiae based matching,

fingerprint image needs to be aligned to find the matching minutiae pairs from probe to gallery templates [21] [22].

3. Ridge feature-based matching: The fingerprints in terms of features extracted from the ridge pattern are compared by the approaches belonging to this family [23] [24] [25].

There are many fingerprint matching algorithms in the literature that are developed using minutia points [26] [27] [28]. Some of the fingerprint matching algorithms have been proposed using the local minutiae descriptors [29] [26] [30] [31]. A few fingerprint matching techniques combine ridge flow orientation with minutiae matching information either at scores level by combining scores from global orientation field matching and minutiae matching [32] [33] or at feature level by including ridge flow features in local minutiae descriptors [34] [32].

Jain et al. [35] have developed a hybrid matching technique that uses ridge features and minutiae information for templates comparison, resulting in improved accuracy. The Gabor filters are used inorder to extract ridge features. Sheng et al. [36] developed a memetic fingerprint matching algorithm (MFMA) for matching of fingerprints from probe against gallery, generated the local features that determine matching in both templates using the degree of alignment. Jie et al. [37], combined minutiae features and core location in matching. The core is the maximum point of ridge curvature in a fingerprint image, and the core served as a reference point in the matching algorithm. The features with close distances from the core point in the probe and enrolled constitute a match. Germain et al. [38], the originator of the minutiae triplet matching technique, used properties of triplets of minutiae to match fingerprints. This method is the most acceptable and state-of-the-art method of local minutiae matching technique.

2.2.6 Recognition of latent fingerprint

The accuracy of latent fingerprint recognition depends on the skill of latent examiners while locating the minutia points on the latent fingerprint. A fingerprint expert is often able to correctly identify the minutiae by using various visual clues such as local ridge orientation, ridge continuity, ridge tendency, etc., as long as the ridge and valley structures are not corrupted completely. The majority of the algorithms developed for fingerprint matching are based on minutiae. The few existing methods on latent fingerprint recognition is discussed below.

Heeseung Choi et. al. [39] proposed an automatic segmentation of latent fingerprints. A new latent fingerprint segmentation algorithm that identifies the region of interest, namely, the friction ridge pattern, and suppresses the background is proposed. The segmentation algorithm utilizes both ridge orientation and frequency features. A flowchart of the proposed method,They considered a fingerprint as a texture pattern (oriented line pattern within a certain valid range of frequency), and utilize both fingerprint orientation and frequency information to segment latents. The main difficulty in latent fingerprint segmentation is the presence of structured noise (e.g., arch, line, character and speckle). The orientation tensor approach is used to extract the symmetric patterns of a fingerprint as well as to remove the structured noise in background. Local Fourier analysis method is used to estimate the local frequency in the latent fingerprint image and locate fingerprint region by considering valid frequency regions. Candidate fingerprint (foreground) regions are obtained for each feature (orientation and frequency) and then an intersection of these regions is used to localize the latent fingerprint region.

Jianjiang et. al. [40] proposed combining minutiae descriptors for fingerprint matching. In this work, they present texture-based descriptors, minutiae-based descriptors and the combination of them. Texture-based descriptors consist of ridge orientation and frequency information at some sampling points around a minutia. Local minutiae structures have been used by many researchers to increase the distinctiveness of minutiae. Two types of representation, fixed-length feature vectors and unfixed-length feature vectors, have been adopted by different researchers to describe local minutiae structures. In this work, local minutiae structures are termed minutiae-based descriptors. Since texture-based descriptors and minutiae-based descriptors capture contemporary information, and further improve the discriminating ability of descriptors by combining two descriptors using the product rule,

$sc = st \times sm$,

where sc, st, and sm represent the similarity of combined, texture-based, and minutiae-based descriptors, respectively. The combined texture based and minutiae-based descriptors can increase the discriminating ability of descriptors.

Anil K. Jain et. al. [41] proposed a system for matching latent fingerprints found at crime scenes to rolled fingerprints enrolled in law enforcement databases. In addition to minutiae, they also use extended features, including reference points (singularity), overall image characteristics (ridge quality map, ridge flow map, and ridge wavelength map), and skeleton. The effect of the secondary features (dots, incipient ridges, and pores) has also been examined. The baseline matching algorithm takes only minutiae as input and performs the three type of matching as follows:

1. *Local minutiae matching*: In local minutiae matching, the similarity between each minutiae of latent fingerprint and each minutiae of rolled fingerprint is compared.

2. *Global minutiae matching*: Given the similarity among all minutia pairs, the one-to one correspondence between minutiae is established in the global minutiae matching stage. The greedy strategy is used to find matching minutia pairs in the decreasing order of similarity.

3. *Matching score computation*: The computation of matching scores is typically approached in two ways, namely, formula-based and classifier-based. In formula-based approach, an empirically chosen formula is used to compute matching scores. In classifier-based approach, scoring is regarded as a two-category clas-

sification problem. A pair of fingerprints is classified by a traditional classifier, such as artificial neural network(ANN) or support vector machine(SVM), as a genuine match or an impostor match based on the feature vector extracted from matching these two fingerprints. In baseline algorithm, the neighboring minutiae-based descriptor is used, since only minutiae information is available. The various extended features indicate that singularity, ridge quality map, and ridge flow map are most effective features in improving the matching accuracy.

2.2.7 Issues addressed in fingerprint recognition

The observations from the review of the existing approaches are that most of these approaches are designed for a single sensor design. Moreover, the existing algorithms are computationally expensive and require a significant amount of memory for matching. Finally, most of the existing latent fingerprint matching algorithms require manually marked minutiae on latent fingerprints for recognition. In this thesis, we attempt to address these issues during the various phases of fingerprint acquisition, feature extraction, and matching. In contrast to existing approaches that consider a single sensor for acquisition, we analyze the performance of fingerprints captured by various authentication sensors using NIST Bozorth algorithm. We propose a global and local adaptive binarization (pre-processing) technique to remove noise from fingerprints and a global minutiae matching algorithm that is tolerant to spurious minutiae for efficient recognition. Unlike majority of existing algorithms using minutiae points with graph techniques (thereby making them memory intensive and computationally expensive), a hybrid matching approach using minutiae quadruplets computed from the candidate minutiae generated by k-nearest neighbors algorithm is proposed. The utilization of only spatial characteristics of the minutiae and the low computational complexity of k-NN algorithm, makes this approach effective in-terms of both space and time. To overcome the need for manually marked minutiae for latent fingerprint matching by existing algorithms, we propose a semi-automated approach that processes a manually marked region of interest to automatically detect the minutiae points. A global minutiae matching algorithm tolerant to missing genuine and spurious minutiae is also proposed to work with the minutiae recognized by the semi-automated approach.

2.3 PALMPRINTS

Palmprint recognition techniques have been grouped into two main categories. The first approach is based on low-resolution features, and the second approach is based on high-resolution features. First approach makes use of low -resolution images (such as 75 or 150 ppi), where only principal lines, wrinkles, and texture are extracted. Second approach uses high resolution images(such as 450 or 500 ppi) , where in addition to principal lines and wrinkles, more discriminant features like ridges, singular points, and minutiae can be extracted.

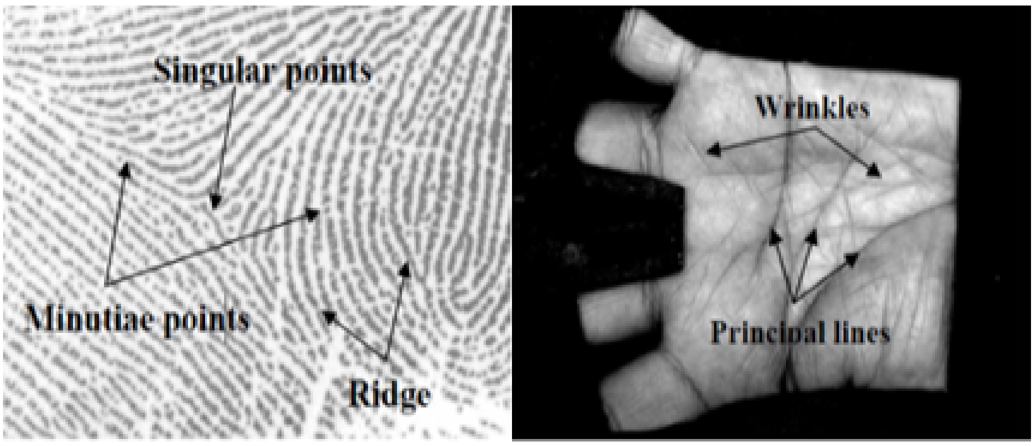


Fig. 2.3: Palmprint features ([42])

Palmprint research employs either high resolution or low resolution images. The high resolution images are suitable for forensic applications such as criminal detection and the low resolution images are more suitable for civil and commercial applications such as access control. Generally speaking, high resolution refers to 400 dpi or more and low resolution refers to 150 dpi or less [42]. Fig. 2.3 [42] illustrates a part of a high-resolution palmprint image and a low resolution palmprint image. the high resolution fingerprint images extract features like, ridges, singular points and minutia points while in low resolution images extract principal lines, wrinkles and texture as features for matching. Initially, palmprint research focused on high-resolution images [43] [44]. The design of a biometric system takes account of five objectives: cost, user acceptance and environment constraints, accuracy, computation speed, and security. The reduction in accuracy can increase the speed of palmprint recognition. Typical examples are hierarchical approaches. Also, the reduction in user acceptance can improve the accuracy of recognition. For instance, users are required to provide more samples for training of the palmprints. We can embed more sensors to collect different signals for liveness detection. In some applications, environmental constraints such as memory usage, power consumption, size of templates and size of devices have to be fulfilled. A biometric system installed in personal digital assistant (PDA) requires low power and memory consumption but these requirements may not be vital for biometric access control systems. A practical biometric system should balance all these aspects.

2.3.1 Early history of palmprint biometrics

Palm print recognition works similarly to fingerprint recognition in that it uses the uneven surfaces of ridges and valleys on ones hand. One advantage of palm print scanning is that it provides a large number of minutiae for comparison, much more than fingerprints alone, which can lead to increased accuracy. The palmprint recognition devices have not been as widely adopted because they tend to be bulkier and more expensive.

Below is the time line of some key dates relating to palm print recognition [45]:

- 1858 - Sir William Herschel records handprints on the back of employee contracts for the Civil Service of India. This is the first recorded systematic capture of hand and finger images for identification purposes.
- 1917 - First time palm prints were used as evidence in a US courtroom. The

bloody palm print left at the scene of a murder in Nevada was identified to Ben Kuhl.

- 1994 - First known automated fingerprint identification system (AFIS) to support palm prints is believed to have been built by a Hungarian company, RECOWARE Ltd.
- 1997 - US company bought Hungarian palm system.
- 2000s - Australia houses the largest repository of palm prints in the world in the Australian National Automated Fingerprint Identification System (NAFIS).
- 2002 - A staff Paper on palm print technology and IAFIS palm print capabilities was submitted to the identification services subcommittee, CJIS advisory policy board (APB).
- 2004 - First statewide automated palm print databases are deployed in Connecticut, Rhode Island, and California.
- 2013 - The FBIs next generation identification (NGI) system deployed the new national palm print system (NPPS) which contains millions of palm prints that are now searchable on a nationwide basis.

2.4 PALMPRINT RECOGNITION SYSTEM

Palmprint recognition got more prominence in last 10 years. During this period, different issues that are related to palmprint recognition have been solved. In this thesis, an efficient palmprint matching technique to match full palm with minutiae quadruplets is proposed.

2.4.1 Line-based approaches

Line-based palmprint matching approaches [42] either develop an edge detectors or use existing edge detection methods to retrieve palm lines [46] [47] [48] [49] [50]. These palm lines are either represented in other formats directly for matching. Wu et al. use Canny edge operator [51] to detect palm lines [52]. The orientation estimations of the edge points are gone into four participation functions representing four directions. At last, the Euclidean distance is utilized as a part of matching. Wu et al. designed two masks to compute the vertical first-order derivative and the second-order derivative of palmprint images [47]. With the rotation of two standard marks, the directional second-order and first-order derivatives can be obtained. They use the zero-crossings of the first-order derivatives to identify the edge points and corresponding directions. The magnitude of the corresponding second-order derivative is considered as the magnitude of the lines. They retain only the positive magnitude because palm lines are valleys. The weighted sum of the local directional magnitude is regarded as an element in the feature vector. This feature is normalized by its maximum and minimum components. As with [52], Euclidean distance is used for matching. Wu et al. propose another algorithm, which use Sobel masks to compute the magnitude of palm lines [48]. These magnitudes are projected along both x and y directions to obtain histograms. These histograms are considered as inputs of hidden Markov models (HMMs). Boles et al. use Sobel masks and thresholds to construct binary edge images [53] and then employ Hough transform to extract the parameters of the six lines with highest densities in the accumulator array for matching.

2.4.2 Subspace-based approaches

Subspace-based approaches [42] are also referred as appearance-based approaches in the literature of face recognition. They use independent component analysis (ICA), linear discriminant analysis (LDA), and principal component analysis (PCA) [54] [55] [56] [57]. The subspace coefficients are regarded as features. The various distance measures and classifiers are used to compare the features. In addition to applying ICA, LDA, and PCA directly to palmprint images, researchers also employ wavelets, Gabor, discrete cosine transform (DCT), and kernels in their methods [54]. Some researchers have developed new subspace approaches and examined them on palmprints [58] [59] [60]. Generally speaking, subspace-based approaches do not make use of any prior knowledge of palmprints.

2.4.3 Statistical approaches

Statistical approaches are mainly global or local statistical approaches. In global statistical approach technique [61] [62], global statistical features are computed directly from the complete transformed images. The moments, centers of gravity, and density have been regarded as the global statistical features. In the local statistical approaches, the image is transformed into another domain and then the transformed image is divided into several sub regions [63] [64]. The local statistics such as variances and means of each small region are calculated and regarded as features. The Gabor, wavelets, and Fourier transforms have been applied to the image. The small regions are commonly square but some are elliptical and circular [65]. In addition to directly describing the local region by statistics, Wang et al. use histograms of local binary pattern as features [66].

2.4.4 Issues addressed in palmprint recognition

The existing approaches to palmprint recognition use global and local minutiae with segmentation for matching. This makes them memory intensive and computationally expensive. To overcome these issues, we propose a new hybrid palmprint matching algorithm using k-nearest neighbors with minutiae quadruplets. Unlike the existing algorithms for palmprint matching which are based on segmentation, the proposed approach uses full palmprint-to-palmprint matching for efficient recognition.

2.5 SUMMARY

This chapter reviewed some of the existing approaches to biometric recognition systems, namely, fingerprint and palmprint recognition. The fingerprint recognition is presented by describing each step in detail. The extraction of robust features for fingerprint and palmprint matching is a challenging problem, due to poor quality fingerprints and palmprints. The fingerprint recognition algorithms that are introduced in the last couple of decades are based on the minutiae points. The existing approaches for all the components of fingerprint and palmprint recognition systems are reviewed. Some research issues arising out of the review of existing methods are identified, which are addressed in this thesis.

CHAPTER 3

CROSS SENSOR FINGERPRINT RECOGNITION USING GLOBAL MINUTIAE MATCHING

Fingerprint biometric is one of the important biometric used to authenticate the users. The various sensors are used to capture the live fingerprint images. The fingerprint image that is captured from the sensor is compared with the fingerprint image stored in the database. If a hit is found, then the access will be given to user. The fingerprint sensors are extensively being implemented in access control systems. The factors such as worn surface, dry skin of the finger, improper contact of fingerprint with the sensor, bright ambient light over the sensors, moisture, scratches, and the dirt on the sensor can result in a bad surface of the finger which in turn effects the quality of the fingerprint captured by the biometric sensor.

A biometric fingerprint scanner can operate on a number of different techniques to scan a fingerprint image, like capacitive scanning, optical scanning or multi-spectral scanning. If the operational circumstances are not optimal, the resulting image can be of poor quality, thus hindering proper authentication. An optical sensor based scanners utilize light to read and obtain unique finger impressions. Optical sensors can be influenced by various other factors stray light, surface sullying or even earlier ghost finger impressions present on the sensor surface. Henceforth, it is key to clean the fingerprint scanner glass all the time for ideal execution. Many optical scanners can detect a live fingerprint from a spoof fingerprint using 'live finger detection' or 'spoof detection'.

The fingerprint images captured by authentication sensors are noisy and small in size, thereby affecting the overall performance. So, we propose a global and local adaptive binarization technique for noise reduction and removal of spurious minutiae. The effectiveness of the proposed adaptive binarization technique with global minutiae matching is analyzed with fingerprints captured from various optical sensors. This chapter is organized as follows: Introduction to sensors and how optical sensor technology works is explained briefly in Section 3.1. Section 3.2 gives the details of related work. In Section 3.3, the proposed pre-processing technique and fingerprint algorithm is presented. Experimental results of the proposed fingerprint algorithm with fingerprints captured from various fingerprint sensors, that are used for authentication are discussed in Section 3.4. Section 3.5 summarizes the study. In the next section, we describe some of the sensing technologies used to capture fingerprints.

3.1 SENSORS

There are mainly four types of fingerprint sensors technologies available, namely, 1) capacitive sensors, 2) optical sensors, 3) thermal sensors, and 4) multi-spectral sensors. The capacitive and optical sensing technologies are discussed below:

3.1.1 Capacitive sensors

Capacitive sensing is a technology, based on capacitive coupling that can detect and measure anything that is conductive or has a dielectric different from air. The cell works in two phases: first, the charge amplifier is reset, shorting input, and output of the inverter. During this phase, output of the inverter settles to its logical threshold. In the second phase, a fixed amount of charge is sinked from the input, causing an output voltage swing inversely proportional to feedback capacitance value. Since feedback capacitance is inversely proportional to the distance of the skin, a linear dependence of output voltage on skin distance is expected. Since the distance between the skin and the sensor identifies the presence of ridges and valleys, an array of cells is used to sample the fingerprint pattern. An array of cells is addressed in a raster mode by means of horizontal and vertical scanners. The chip also contains timing control and voltage references. The capacitive sensing technology is as shown in figure 3.1 [67].

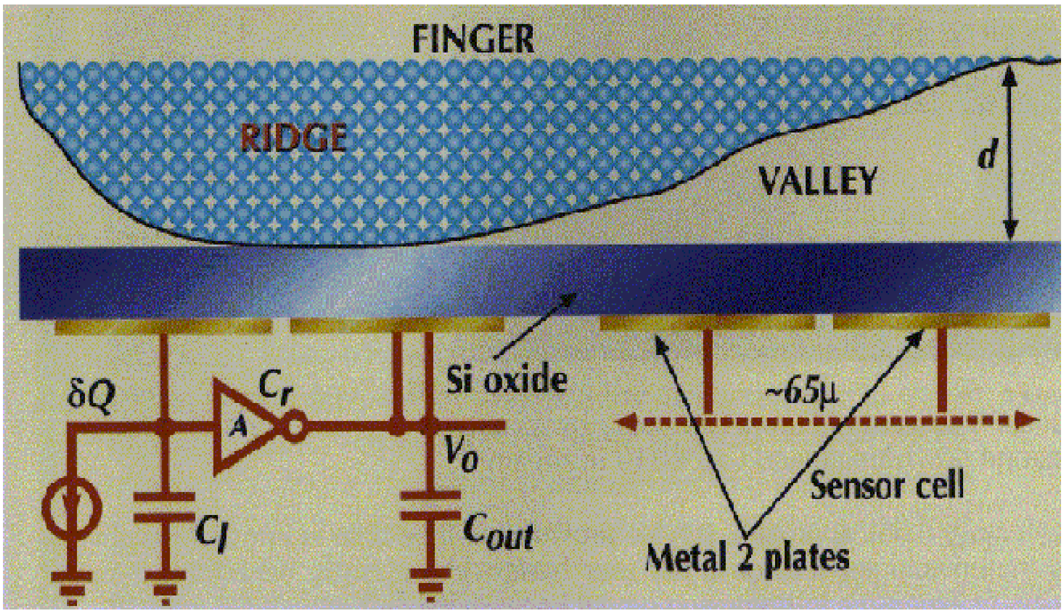


Fig. 3.1: Capacitive sensing technology ([67])

3.1.2 Optical sensors

The key element of an optical scanner is a charge coupled device (CCD), the light sensor that is used in camcorders and digital cameras. An array of light-sensitive diodes called photosites form a CCD, which generates an electrical signal in response to light photons. Each photo site records a pixel, a tiny dot representing the light that hit that spot. Collectively, the light and dark pixels form an image of the scanned scene (a finger, for example). Typically, an analog-to-digital converter in the scanner system processes the analog electrical signal to generate a digital representation of this image. The optical sensor technology is shown in the figure 3.2 [68].

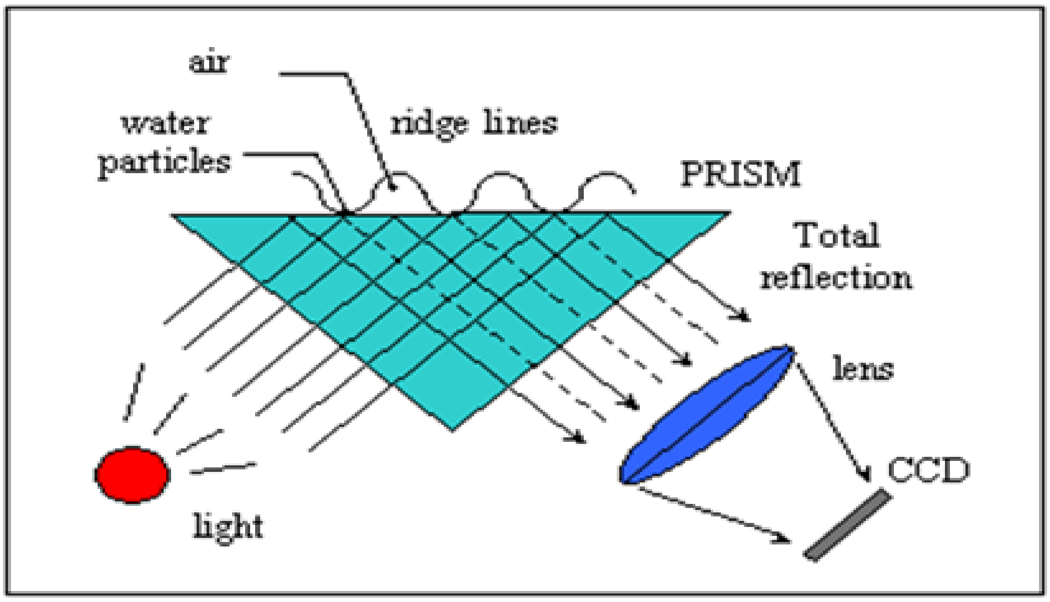


Fig. 3.2: Optical sensing technology ([68])

In this chapter, a fingerprint matcher is proposed which uses the global and local adaptive binarization in pre-processing stage of minutiae extraction and global minutia features for comparison in the matching. The fingerprint data is collected using three different authentication devices based on optical sensors. The experimental results are compared with the National Institute of Standards and Technology (NIST) Bozorth algorithm and various authentication fingerprint sensors.

3.2 RELATED WORK ON FINGERPRINT MATCHING

A fingerprint consists of ridges and valleys on the surface of the finger. The uniqueness of a fingerprint can be determined by the minutia points. Minutia points are the local ridge features which are identified by a ridge bifurcation or a ridge ending. Fingerprint matching is a difficult problem due to its large intra-class variations and small inter-class variations. Intra-class variations mean the variation of same finger among different fingerprints, whereas inter-class variations are the similarity among different fingerprints. The reasons for intra-class variations are partial overlapping of fingerprints and noise formed from sensors. There are three main categories of fingerprint matching algorithms, which are correlation based, minutia based, and ridge orientation based approaches. The methods described in [69] [70] [71] [72] [73] [74] use various filtering techniques to enhance the significant details of single fingerprint images. The fingerprint segmentation using block-wise grey-level variances or local histograms of ridge orientations were described in [75]. In [76], Gabor filters are used to divide a fingerprint into foreground and background regions. The de-noising of fingerprint images was presented in [77].

Kaur et al. [78] have introduced the methods combined to create the minutia extractor and minutia matcher. Tarjoman et al. [79] introduced structural approach to fingerprint classification by using the directional image of fingerprints instead of singularities. The detection of singularities is used to increase the accuracies. Wei et al. [80] proposed a method for rapid singularities searching which used the delta field Poincare index and a rapid classification algorithm to classify the fingerprint into five classes. The detection algorithm searches the direction field which changes more largely to get the singular points. The singular point detection is used to improve the accuracy. Lumini et al. [81] developed a method for the minutia based fingerprint and its approach to the problem as two-class pattern recognition. The feature vector obtained by minutia matching is classified into genuine or imposter using a support vector machine (SVM) resulting remarkable performance improvement. Tong et al. [82] proposed a method to overcome nonlinear distortion by using local relative error descriptor (LRLED). This algorithm consists of three steps: 1) A pair wise alignment method to achieve fingerprint alignment; 2) A matched minutia pair set is obtained with a threshold to reduce non-matches; and 3) The LRLED based similarity measure. LRLED is good at distinguishing between the matched and non-matched minutia pairs and works well for the minutia based matching. Jain et al. [83] proposed a latent fingerprint matcher based on local and global minutia matching using the similarity between latent and rolled/plain fingers. Li et al. [84] have proposed the extended cross matching algorithm for the fingerprint images captured from different sensor technologies, namely, optical, capacitive, and thermal sensors. Some researchers proposed fingerprint identification techniques using a gray level watershed method to find the ridges present on a fingerprint image by directly scanning the inked fingerprint impressions.

The sensors used for fingerprint authentication are small in size, resulting in small fingerprint images. As a result, the effectiveness of the matching approach using these images deteriorates significantly. To overcome this issue, we propose a global fingerprint matching algorithm using global and local adaptive binarization in the pre-processing stage and global minutia features at matching stage. The experiments are conducted on the fingerprint data which are captured using personal identity verification (PIV) certified authentication devices [85]. The algorithms have two different phases, one is for finding the number of matched minutia and the other phase is for validating the correctness of matching. The fingerprint data is collected using Cogent-200, BioMini-Plus, and Upek. These devices are currently under testing for the authentication applications supported by Aadhaar [85]. The data is collected from 30 subjects 10 fingerprints in five instances. Fig. 3.3 shows the images captured using the Cogent fingerprint authentication device. Fig. 3.8 shows the images captured using the Bio-Mini fingerprint authentication device. Fig. 3.9 shows the images captured using the Upek fingerprint authentication device. The image dimensions for the images captured by cogent device is 340×480, by bio-mini device is 260×340, and by upek is 256×360. All the images are captured at 500 dpi.

Fig. 3.3: Fingerprints captured from cogent CSD200

Fig. 3.4: Fingerprints captured from suprema biomini

Fig. 3.5: Fingerprints captured from upek

3.3 LOCAL AND GLOBAL ADAPTIVE BINARIZATION

Local and global adaptive binarization is the process that combines local mean intensity as well as global mean intensity information to binarize the fingerprint image. This combination works very well for the noisy finger prints that are captured on the fingerprint scanners, where the previous fingerprints residue is left as a ghost image on the surface of the fingerprint scanner. The global mean intensity is computed as the sum of all the pixel intensity values divided with the total number pixels present in the image. The global binarization uses the global mean intensity as the threshold to binarize the fingerprint image, whereas the local adaptive binarization uses the mean intensity of each 88 block from the fingerprint image and binarizes the particular block of corresponding local mean intensity value. The proposed binarization combines both the global binarization as well as local adaptive binarization. Fig. 3.6 illustrates the comparison of the traditional binarization given by National Institute of Science and Technology (NIST) and the proposed binarization. The proposed binarization removes the spurious minutia which is formed due to the ghost images and improves the accuracy of fingerprint feature extraction.

The figure 3.7 illustrates the minutia display which is implemented using the NIST binarization and the global and local adaptive binarization. The feature extraction algorithm which is used for minutiae display is a NIST open source. The NIST feature extractor is little sensitive in detecting minutia and there is a need to remove the border minutiae in order to improve accuracy.

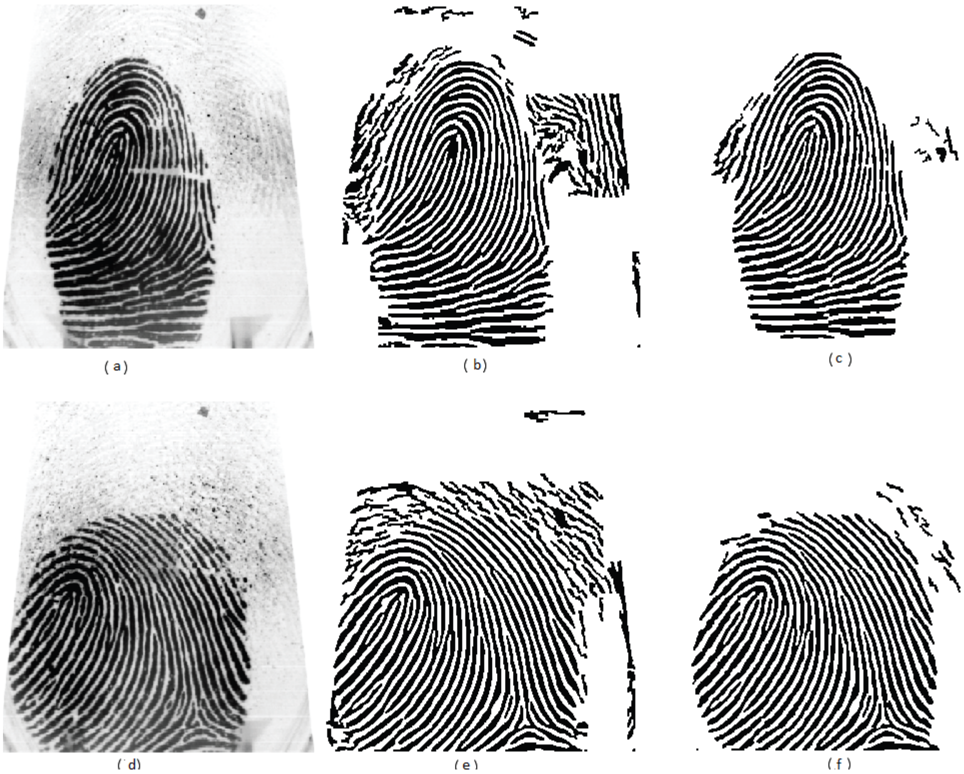


Fig. 3.6: Images in the first column are original images, images in the second column are the NIST binarized images, and images in the third column are of trained using the proposed binarization.

Fig. 3.7: Minutia (feature) extraction: left side images are obtained using NIST binarization and right side images are obtained using the proposed binarization.

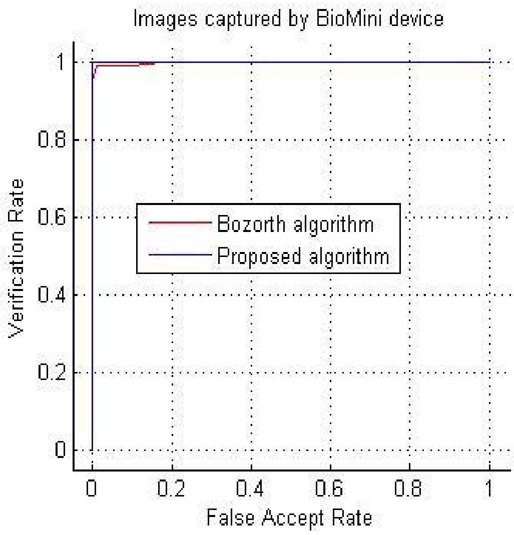
3.4 EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we used global and local adaptive binarization technique in binarization to improve the accuracy of template extraction and global minutia features in the matching. The fingerprint data is collected using three different authentication devices based on optical sensors. The proposed fingerprint matching algorithm uses ISO (International Organization for Standards) fingerprint templates which are extracted by NIST fingerprint template extractor. Algorithm 1 gives the steps involved in the global minutia matching. The feature vector consists of the information: x, y-coordinates and direction of each minutia.

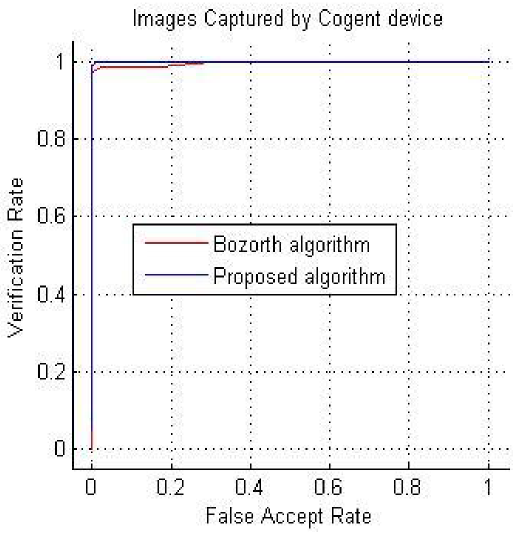
Algorithm 1 Proposed global minutiae matching algorithm

1. Query and reference ISO templates as input.
2. Get the query and reference templates X, Y, Direction, Type and Quality.
3. Compute the edge pair information for each minutia to all other minutia
4. Sort the edge pair information using distance.
5. Compute the similarity of edge pair information in query and reference templates for similarity.
6. Validate the matched minutia pairs with all other matched minutia pairs to remove false matched minutia pairs.
7. Compute the matching score

The cross-sensor fingerprint matching experiments are conducted using the database collected with three different live-scanners (Biomini, Cogent and Upek). The plain fingerprint data consists of all the 10 fingerprints of 30 subjects captured at 5 different instances. The proposed cross-sensor fingerprint matching algorithm is evaluated and compared with NIST Bozorth algorithm. Fig. 3.8(a) illustrates the performance of Bozorth and proposed fingerprint matcher algorithm using biomini captured fingerprints. Similarly, Fig. 3.8(b) presents the performance of proposed and Bozorth using fingerprints captured through cogent. Fig. 3.9(a) illustrates the performance of Bozorth and proposed fingerprint matcher algorithm using fingerprints captured from upek sensor. Similarly, Fig. 3.9(b) presents the performance of proposed and Bozorth algorithms using fingerprints captured through all the three devices. Fig. 3.10(a) illustrates the performance of Bozorth fingerprint matcher algorithm using four different scenarios of data. Similarly, Fig. 3.10(b) presents the performance of proposed cross-sensor fingerprint matcher algorithm using the four different scenarios of fingerprint data. It can be observed that the proposed approach performs very well even with the fingerprint images captured using the cross-sensor fingerprint authentication devices. Experimental results show that the proposed technique achieves the equal error rate (EER) at 0.02 whereas the existing NIST open source Bozorth matching algorithm has the EER is at 0.15. Table 3.4 illustrates the equal error rates (EER) of Bozorth and proposed fingerprint matcher algorithms on cross-sensor authentication devices.



(a)

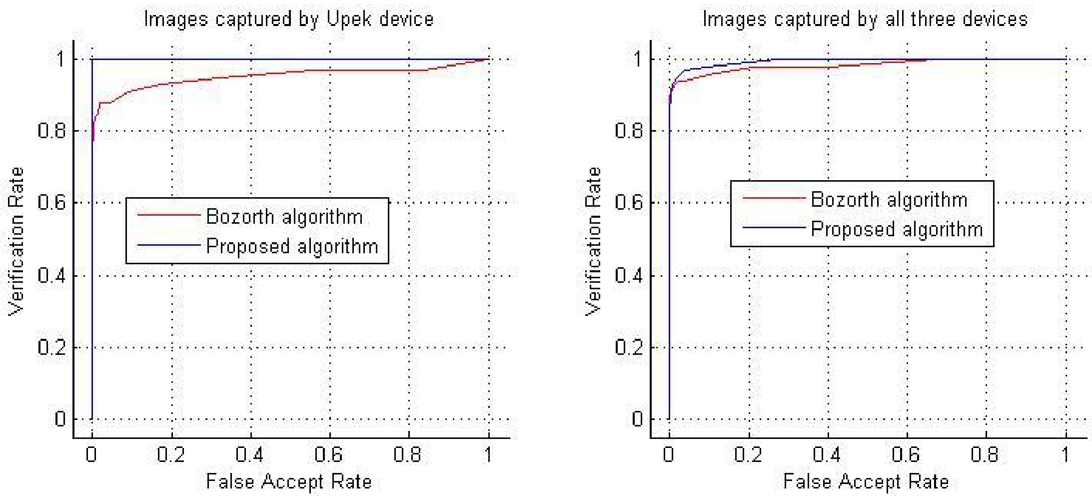


(b)

Fig. 3.8: (a) Analysis on Bozorth and proposed matcher using the images captured with biomini device, (b) Analysis on Bozorth and proposed matcher using the images captured with Cogent CSD200 device

Table 3.1: Performance comparison of the proposed fingerprint method with Bozorth approach

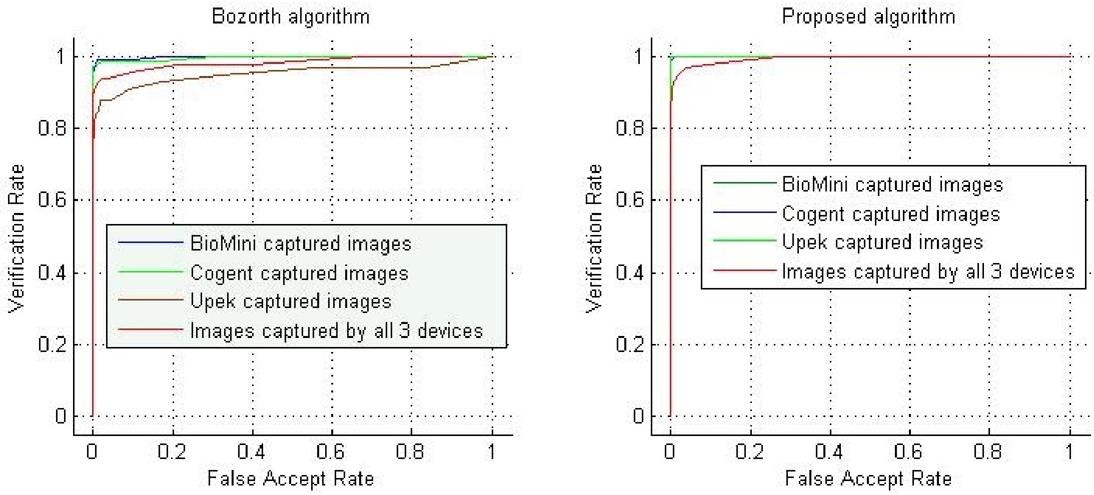
Sensor Used	**Bozorth EER (%)**	**Proposed Matcher (%)**
All three devices (cross sensed)	0.05	0.02
Suprema BioMini	0.01	0.001
Cogent CSD200	0.02	0.005
Upek	0.09	0.001



(a)

(b)

Fig. 3.9: (a) Analysis on Bozorth and proposed matcher using the images captured with Upek device, (b) Analysis on Bozorth and proposed matcher using the images captured by all the three devices



(a) (b)

Fig. 3.10: (a) Analysis on Bozorth matcher using the images captured by all the three devices, (b) Analysis on proposed matcher using the images captured by all the three devices

3.5 SUMMARY

In this work, the performance of various optical fingerprint sensors is analysed using NIST Bozorth and global minutiae based fingerprint matching algorithms. The experimental study suggests that the proposed global minutiae matching technique is resilient to rotation and translations. The proposed algorithm achieves EER of 0.02 where NIST Bozorth algorithm has an EER of 0.05. The results also suggest that the placement (location and orientation) of fingers impacts the recognition accuracy irrespective of the size of the sensor used to capture fingerprints.

CHAPTER 4

HYBRID FINGERPRINT MATCHING TECHNIQUE ON PLAIN FINGERPRINTS

The problem of cross sensor fingerprint recognition is discussed in the previous chapter, using adaptive binarization with global minutiae matching. A fingerprint (plain) [86] is the most widely used biometric trait. A fingerprint can be uniquely identified by the minute details called minutia points. These points can be identified by the local ridge features, namely, a ridge bifurcation and a ridge ending. Most of the algorithms are based on combination of minutiae and ridge features, that use more memory while matching, thereby increasing the computation time. In this chapter, we aim to optimise the resource (space and time) utilization of fingerprint matching algorithms by using only a few characteristics of minutiae points. We propose a hybrid fingerprint matching algorithm using k-nearest neighbor matching and minutiae quadruplets with few characteristics of minutiae points for effective resource utilization.

This chapter is organized as follows: In Section 4.1, fingerprint recognition techniques are introduced. Section 4.2 briefly discusses the existing fingerprint matching algorithms. In Section 4.3, hybrid fingerprint matching using k-nearest neighbors and minutiae quadruplet is explained. In Section 4.4, experimental results of the proposed hybrid fingerprint matching algorithm are discussed. Section 4.5 summarizes the study.

4.1 INTRODUCTION

There are three different approaches in fingerprint matching, namely, minutiae-based [87], ridge feature-based [88], and correlation-based [86]. Minutiae-based fingerprint matching methods find number of minutiae matches between the input fingerprint (probe) and the enrolled fingerprint (gallery). This is the most popular and widely used approach. In the correlation-based fingerprint matching, two fingerprint images are overlapped and the similarity between corresponding pixels is determined for the different alignments. This kind of matching is computationally expensive and prone to distortions in the images. In ridge feature-based fingerprint matching, features of the fingerprint ridge patterns like local ridge orientation, frequency, and shape are extracted for comparison. These features may be more reliable for comparison in fingerprints of low-quality images than minutiae features. The matching of the fingerprint matching algorithm is correct when there are genuine matches (true accepts) and genuine rejects (true non-matches). The matching is wrong when there are impostor matches (false accepts) and impostor non-matches (false rejects). The performance of fingerprint recognition is not 100% efficient due to noise, common area, template extraction and matching. The important issue is to limit the errors false accept rate (FAR) and false reject rate (FRR) as much as possible.

Earlier, the fingerprints were widely used for criminal investigation systems, but now the fingerprint recognition systems play a key role in civilian applications in order to provide public services and welfare schemes for the benefit of the people in the society. The large population person identity programs (for example India's Aadhaar and UAE's border security programs) choose the fingerprint biometrics as one of the source of person authentication. The fingerprint matching algorithm is the key component in fingerprint recognition systems. In the context of large scale fingerprint recognition systems, the fingerprint matching system should utilize the minimum computational complexity and memory space, otherwise the system faces scalability issues.

4.2 EXISTING FINGERPRINT MINUTIAE MATCHING METHODS

Large intra-class difference is the major problem that we face in matching fingerprints. Intra-class variation refers to the large variability in different impressions of the same finger. There are many reasons that lead to such high intra-class variation:

- *Global transformations*: The same finger may be placed at different locations or may be rotated at different angles with respect to the sensor surface during different acquisitions. This can result in a global translation or rotation of the fingerprint area. Any good algorithm has to account for global transformation like translation, rotation, scale, and shear. The effect of these global transformation is as shown in Figure 4.1.

Fig. 4.1: Global transform of two different impressions of the same finger from the FVC 2004 database.

- *Partial overlap*: These global transformations mentioned above often cause part of the fingerprint area to fall outside the sensors field of view, resulting in a smaller overlap between the foreground areas of the two fingerprints. In simpler terms, a lot of minutiae points present in one fingerprint may not be present in the other fingerprint. Dealing with these missing or spurious minutiae points is a major challenge for most of the fingerprint matching techniques. The effect of these partial overlap is as shown in Figure 4.2.

Fig. 4.2: Partial overlap of two different impressions of the same finger from the FVC 2004 database.

- *Non − linear distortions* : Non-linear distortion refers to the compression or stretching of skin due to skin plasticity. This comes up as we try to map the 3D shape of a fingerprint onto the 2D surface of the sensor. The components of the force that are non-orthogonal to the sensor surface produce non-linear distortions. These distortions are quite local in nature and handling these distortions is a major open challenge. There are other reasons also which lead to these distortions [6]. These include the sensor orientation with respect to the finger, the applied pressure, the disposition of the subject, the motion of the finger prior to its placement on the sensor, the skin moisture, and the elasticity of the skin. Also, some users apply excessive force to create intentional elastic deformations. The effect of these non-linear distortions is quite large as shown in Figure 4.3.

- *Pressure and skin condition* : We would ideally want to capture the ridge

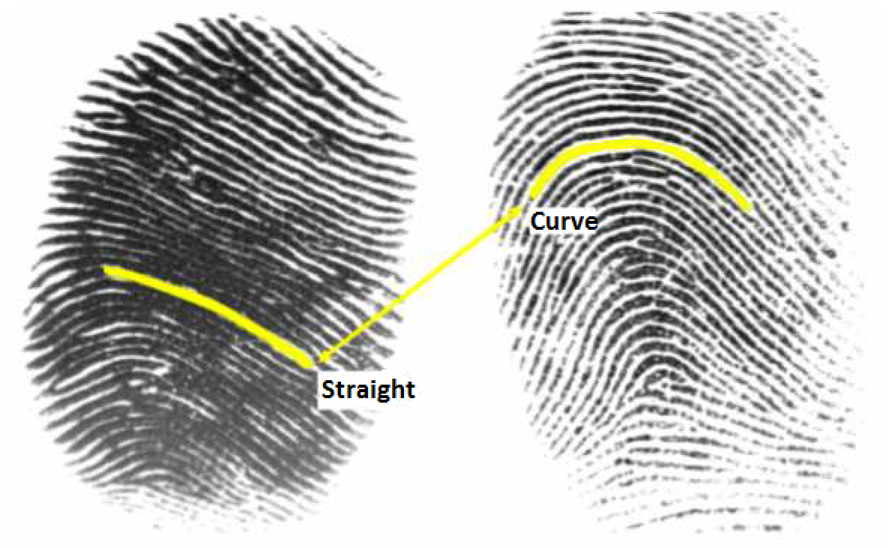


Fig. 4.3: Non-linear distortion of two different impressions of the same finger from the FVC 2004 database.

structure of a fingerprint with high accuracy. For this, part of the finger being imaged has to be in uniform contact with surface. But in real life, because of pressure, dryness, skin disease, sweat, dirt, humidity etc, we get a non-uniform contact and hence a noisy image. Such noisy images result in a lot of spurious minutiae points which the algorithm has to deal with. The effect of fingerprint pressure over fingerprint sensors is as shown in Figure 4.4.

4.2.1 Correlation-based matching

The correlation based matching methods usually work directly on fingerprint images by superimposing the two images and computing the correlation between the corresponding pixels for different alignments. Usually, a cross-correlation measure representing similarity between the two images (like sum of squared difference of intensity values) is computed. But the direct computation of correlation is not a good solution because of the following reasons :

- Two global fingerprint patterns cannot be reliably correlated because of non-linear distortions.

Fig. 4.4: Different pressures of two different impressions of the same finger from the FVC 2004 database.

- Skin condition and finger pressure cause the images brightness, contrast, and ridge thickness to vary significantly across different impressions of the same finger. So, the plain simple correlation of pixels will not give very good result in this case.
- Pixel correlations have to be computed for many alignments. Since, the space of possible alignments is exponential with respect to the number of minutiae, correlation based methods are very expensive.

4.2.2 Ridge features based matching

Global features such as singular points, orientation flow around core points, Poincar'e index and average ridge-line frequency represent the global pattern of ridges with uniform model. Many techniques like Tico in [89], Medina-Perez in [90], G.Ngand X.Tong in [91] and Wang in [92] use global orientation flow and frequency for matching purposes. Many methods also use spatial relationship and geometrical attributes of the ridge lines [93]. Y.He and J.Tian use global texture information present in the fingerprint in their work [94]. Unfortunately, most of the global matching algorithms are computationally demanding and lack robustness with respect to non linear distortions. Another major issue is that most of these global features are not present in the standard ISO/IEC 19794-2(2005) minutia template and have to be computed separately starting with the original image. Many of above techniques [95] require prior alignment of the two fingerprint images which is computationally expensive. Since non-linear distortions make impressions of the same finger differ in terms of global structure, these techniques are not able to handle local non-linear distortions. Local minutiae based fingerprint matching methods generally outperform their global counterparts. However, global features are good for the task of fingerprint classification or can be used in conjunction with more discriminative and robust minutiae based features.

4.2.3 Minutiae based

Minutiae based techniques are the most popular due to the compactness of the minutiae templates and also because these are the features that fingerprint experts look at while doing the visual inspection of fingerprints. Minutiae are extracted from the two fingerprints and stored as a set of points in 2-D space. The problem now reduces to 2D point pattern matching problem. Minutiae based matching methods can be further broken down into global and local minutiae matching methods. Global methods [95] search the space of possible transformations to find a global alignment between the two fingerprints that results in the maximum number of minutiae pairings. Hough transform based techniques fall in this category. Non-linear distortions is a major issue with these techniques. Also, the number of alignments can be exponential (w.r.t number of minutiae) and hence, these techniques are quite slow in practice. Local minutiae matching methods construct local minutiae structures around each minutia point. Then the two fingerprints are compared according to these local structures. These methods use relative distances and angles between neighboring points and the minutia point to construct the local structures. These attributes (relative distances and angles) are invariant with respect to global transformations such as translation, rotation, scale and shear, and therefore can be used for matching without any a priory global alignment. These local structures can also handle non-linear distortions better than global minutiae matching techniques. Some techniques such as [96] [97] [98] use local structures around minutiae points for the purpose of matching. These local structures are described in detail in the next section.

There are mainly two types of minutia matching involved with minutiae-based matching, one is with local minutiae and another one with global. In global minutiae matching, highly discriminative features of the fingerprint are used for comparison. The least distance between minutiae in the probe and enrolled fingerprint is determined, whereas in local minutiae matching, structures are defined based on some geometric or feature based technique which can be used in comparing fingerprint images for matches or non-matches. The global matching is accurate but has high computational complexity, low distortion tolerance, heavy template size, and slow speed of computation.

Local matching techniques on the other hand do not need highly distinctive features. They have a low computational complexity and small template size since the features are based on some secondarily derived structures for matching. The fingerprint matching can be done using the Hough transform which is a normally used approach in global matching. Several authors have developed local matching techniques using k-nearest neighbor technique for comparing fingerprints.

4.2.3.1 Fixed radius based structures

In the fixed radius based structures, all the minutiae points that lie inside the sphere of given radius R (with central minutia as the center) for the neighborhood in that central minutia. Again, normal Euclidean distance is considered for measuring distance.

A novel graph representation of a fingerprint, based on fixed radius of local structure (shown in Figure 4.5 [99]) is proposed by Ratha and Pandit [99]. They call their

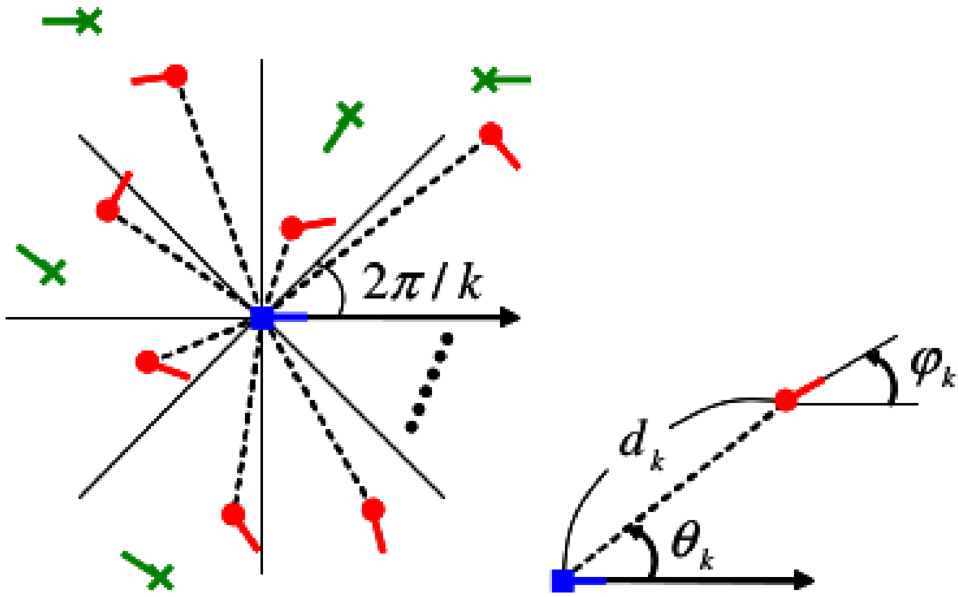


Fig. 4.5: The k-directional nearest neighbor (k-DNN) structure proposed by Kwon (for k=8). The red minutiae points represent the nearest points in each slot and the green minutiae points represent the second nearest ([99])

representation minutiae adjacency graph (MAG) and present a robust and accurate matching technique for MAGs based on local structural similarity. However, like most of the fixed radius based approaches, their method does suffer from border errors. The major issue is in handling of the minutiae that lie on the boundary of the sphere. In particular, minutiae close to the local-region border in one of the two fingerprints can be mismatched because local distortion or location inaccuracy may cause the same minutiae to move out of the local region in the other fingerprint. The technique proposed by Feng [93] does not suffer from border errors and can be considered a state-of-the-art fixed radius local matching algorithm. They deal with the border problem by considering minutiae not close to the border as matchable and minutiae near the border as should-be-matchable. Most of the fixed radius based approaches lead to a variable length descriptor (since the number of minutiae in the sphere will depend on the minutiae density around the central minutia) which is more complex to match.

4.2.3.2 Minutiae cylinder code

Hybrid structures usually combine the advantages of both nearest neighbor-based and fixed-radius structures, without suffering from their respective drawbacks. The minutiae cylinder code (MCC) [100] is the state-of-the-art approach in this area. The minutiae cylinder code is a fixed-radius approach and therefore, it can handle missing/spurious minutiae better than nearest neighbor-based approaches. But unlike other fixed-radius approaches, MCC outputs a fixed length descriptor for each minutia and this makes the computation of local structure similarities very simple. In fact, the cylinder matching is very simple and fast. It reduces to just a sequence of bit- wise operations (AND, XOR) that can be efficiently implemented even on very light CPUs. The minutiae cylinder code also handles border errors and local non-linear distortions gracefully.

In MCC, the local structure for each minutia m is represented by a cylinder of radius R and height 2π whose base is centered at (x_m,y_m), the 2D location of minutia m. The cylinder is enclosed inside a cuboid whose base is aligned according to the minutia direction Θ_m. The cylinder is divided into sections : each section corresponds to a directional difference in the range $[-\pi,\pi]$. These sections are discretized into $NC = NS \times NS \times ND$ cells as shown in the Figure 4.6 [100]. During the creation of the cylinder, a numerical value is calculated for each cell, by accumulating contributions from minutiae in the neighborhood of the projection of the cell center onto the cylinder base. A fixed radius $3 \times S$ is used to define the radius of the neighborhood. While calculating the contributions, only relative distances and directional differences are used between minutiae. The contribution of each minutia mt to a cell (of the cylinder corresponding to a given minutia m) depends both on spatial information (how much mt is close to the center of the cell) and directional information (how much

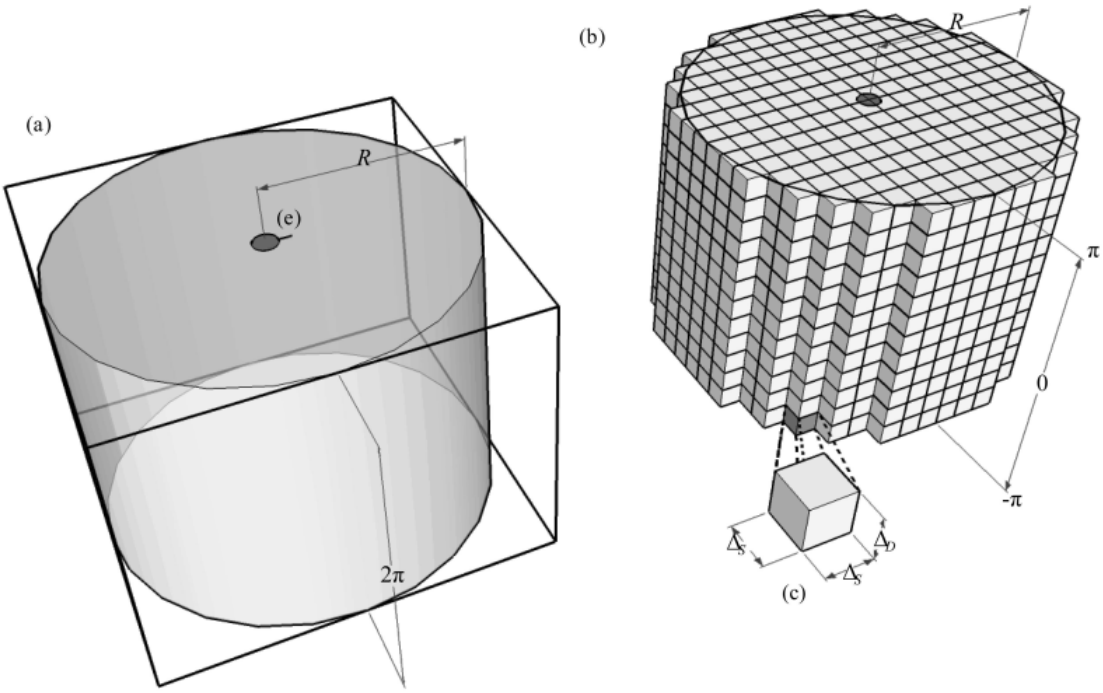


Fig. 4.6: Minutia Cylinder Code structure. (a) The main cylinder is shown enclosed in the cubiod. (b) The cylinder structure is discretized into sections and sections are divided into cells. (c) An individual cell is shown, for each cell a numerical value is calculated from its neighboring minutiae ([100])

the directional difference between mt and m is similar to the directional difference associated to the section where the cell lies).

In other words, value of a cell represents the likelihood of finding minutiae that are close to the cell and whose directional difference with respect to m is similar to a given value. Since, the number of cells are fixed NC, this leads to a fixed length descriptor that can be easily matched. But there are some weaknesses present in the MCC structure also. Their representation of a minutiae neighborhood is not probably invariant to affine deformations. Recently, many attempts have been made at reconstructing a minutia template starting from a minutia cylinder set. Many of these attempts have been quite successful, which puts a question mark on the degree of non-reversibility of MCC representation. The MCC is a fixed length representation for a minutia point and not for the fingerprint. We have local similarity scores representing how well two minutiae points match. But in order to compare two fingerprints, a single value (global score) denoting an overall similarity has to be obtained from these local similarities. Hence, an extra global consolidation stage is required. Also, a minutiae representation of a fingerprint cannot be applied directly in the recently developed template protection schemes such as [101] [102], which require as an input a fixed-length feature vector representation of fingerprints. Many attempts have been made to come up with such a fixed-length representation which is invariant to global transformations but still the problem is far from solved.

The minutiae cylinder code and fixed radius based matching algorithms discussed above require a significant amount of memory during matching. So, we propose a matching algorithm that uses few characteristics of minutiae points, thereby reducing the memory required for matching.

4.3 PROPOSED HYBRID FINGERPRINT RECOGNITION

Let A be the set of fingerprint minutiae and the n-quadruplets can be computed as follows. The k-nearest neighbors from the set A are computed for all $m \in A$ in order to find all n-quadruplets which have m and three of its nearest minutiae which are tolerant to the low quality. Fig 4.7 illustrates the sample quadruplet representation of minutia points. Fig 4.8 illustrates each minutiae pair features for matching, where ab is the Euclidean distance , α is direction at minutiae A, and β is direction at B.

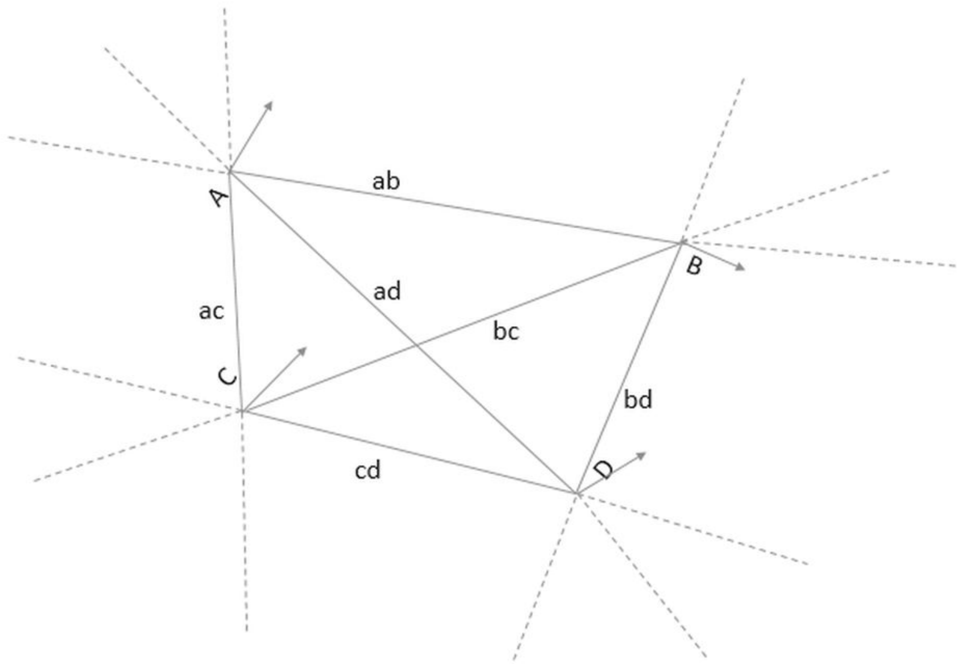


Fig. 4.7: Quadruplet representation of minutiae

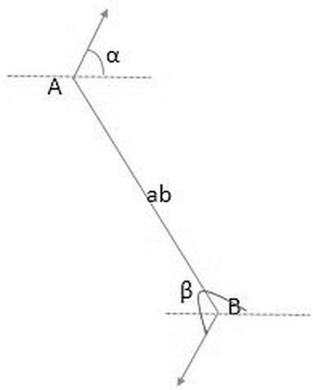


Fig. 4.8: Characteristics of minutiae pair

The Euclidean distances between each pair of minutia are represented in Fig. 4.7 as ab, bc, cd, da, ad, and bc. Each minutia point consists of 5 characteristics x, y, *direction*, *type* and *quality*. In this work, we consider only x, y, and direction for matching and discarded type and quality as these parameters are not significant in matching.

The Euclidean distance between minutiae a and b is given as

$$Dist_{ab} = \sqrt{(x_a - x_b)^2 - (y_a - y_b)^2}, \tag{4.1}$$

where $Dist_{ab}$ is Euclidean distance between minutiae points a and b, x_a is co-ordinate x of minutiae point a, y_a is co-ordinate y of minutiae point a, x_b is co-ordinate x of minutiae point b, and y_b is co-ordinate y of minutiae point b.

The direction difference between minutiae a and b is defined as

$$Dir_{ab} = \arctan \frac{(y_a - y_b)}{(x_a - x_b)}, \tag{4.2}$$

where Dir_{ab} is direction difference between minutiae points a and b.

4.3.1 k-nearest neighbor matching algorithm

The Algorithm 2 finds the similar mates from query template and probe template using k-nearest neighbor local minutia matching techniques. If P and Q are probe and reference minutia set, then the probe minutiae point P and query minutiae point Q are defined as $P_{1..m} = \{Dist_p, Dir_p\}$, and $Q_{1..n} = \{Dist_q Dir_q\}$, where $Dist_p$ is the Euclidean distance to nearest minutiae points, and Dir_p is the direction difference with nearest minutiae points

4.3.2 Global minutiae matching using minutia quadruplets

This step uses each minutiae pair as reference pair for quadruplet calculation. Now, we will form the quadruplets using each minutia to all other minutia. If some quadruplet are formed, then the score will be increased. The following three conditions should be considered to determine whether the two minutiae at global level are matching in order to overcome the tolerance to distortions:

1. Euclidean distance between two minutiae $<$ threshold $DistThr$.

Algorithm 2 k-nearest neighbor matching algorithm

1. Input query and reference ISO templates.

2. Get the query and reference templates X, Y, direction, type, and quality.

3. Compute the edge pair information for each minutia to all other minutia.

4. Sort the edge pair information using Euclidean distance.

5. Find the mates for each minutia in query and probe template using k-nearest neighbors (k= 7,8,9 and 10), using Euclidean distance and direction difference.

6. Let P and Q be the fingerprint minutia of probe and gallery images, respectively, and R and S be the minutia edge pair information. Let M be the set of local minutia pairs which are matched from query and probe template.

7. Sort minutia pair information in query and probe in ascending order using Euclidean distance.

8. Find the similarity from R to S using nearest k-neighbors (6,7,8 and 9) with distance and direction parameters.

2. Difference between minutia directions < direction threshold $DirDiff$.

3. Direction differences relative to reference minutiae pair < threshold $SlpDiff$.

4.4 EXPERIMENTAL RESULTS

The experiments are conducted on the standard fingerprint benchmark data, FVC ongoing competition [103]. The FVC data benchmark statistics for ISO matching and proprietary matching are described in the Table 4.1. Accuracy indicators of the proposed algorithm published on FVC ongoing data is given in Table 4.2 and 4.3.

Table 4.1: FVC ongoing data benchmarking for ISO matching and verification

Scanner Type	**Attempt**	**Comparisons**
Optical	Genuine	27720
Optical	Impostor	87990

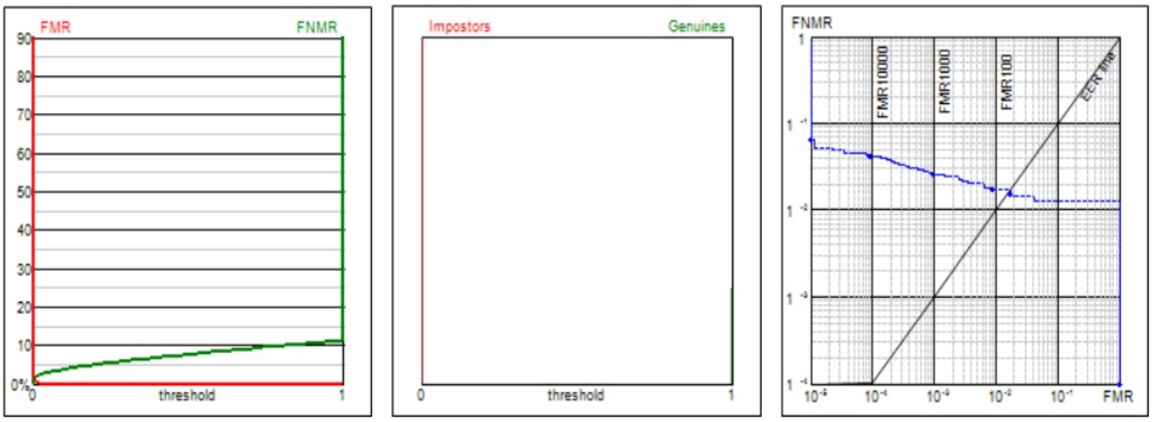
Table 4.2: Accuracy indicators of the proposed algorithm on FVC ongoing data in Fingerprint Matching

EER(%)	FMR_{100}(%)	FMR_{1000}(%)	FMR_{10000}(%)	FMR_{Zero}(%)	$FNMR_{Zero}$(%)
1.322	1.742	2.615	4.242	6.573	100

Table 4.3: Accuracy indicators of the proposed algorithm on FVC ongoing data in Fingerprint Verification

EER (%)	FMR_{100}(%)	FMR_{1000}(%)	FMR_{10000}(%)	FMR_{Zero}(%)	$FNMR_{Zero}$(%)
1.037	1.126	2.731	4.978	6.865	100

The graphs FMR vs. FNMR, score distributions, and DET on FVC ongoing data in ISO matching are illustrated in Figs. 4.9(a), 4.9(b), and 4.9(c), respectively [104]. The graph from FVC shows that the EER is at 1.322 % on FVC ongoing database with the FVC feature extractor and the proposed matching algorithm, achieves reduced space and time due to considering of few minutiae characteristics. The graphs FMR vs. FNMR, score distributions and DET on FVC ongoing data in fingerprint verification is illustrates Figs. 4.10 [105]. The graph from FVC shows that the EER is at 1.037 % on FVC ongoing database with the proposed feature extractor and matcher combination, and have achieves reduced space and time, the proposed feature extractor is using advanced pre-processing techniques.



(a) (b) (c)

Fig. 4.9: Results on FVC ongoing: (a) FMR(t) and FNMR(t) graphs (b) Score distributions (c) DET graph ([104])

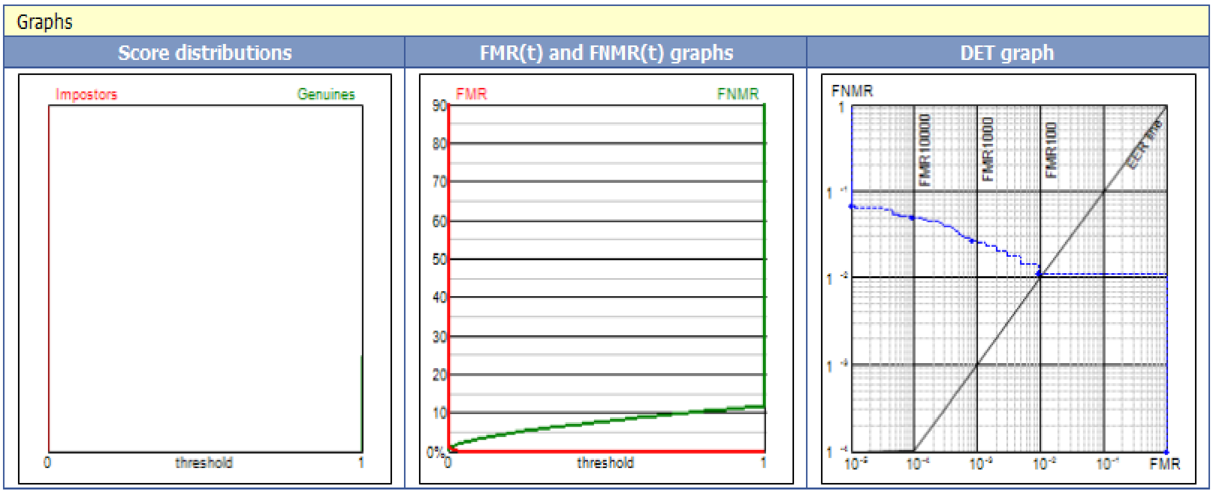


Fig. 4.10: Results on FVC ongoing fingerprint verification: score distribution, FMR(t) and FNMR(t) and DET graph ([105])

Figure 4.11 gives an example of the failed matching pair of fingerprint images. The failure is mainly due to less common area from probe finger image to gallery finger image due to very few common minutiae. Figure 4.12 gives an example for successful matching pair of the fingerprint images. This is due to the common area from probe finger image to gallery image is good enough to match, resulted in very good score.

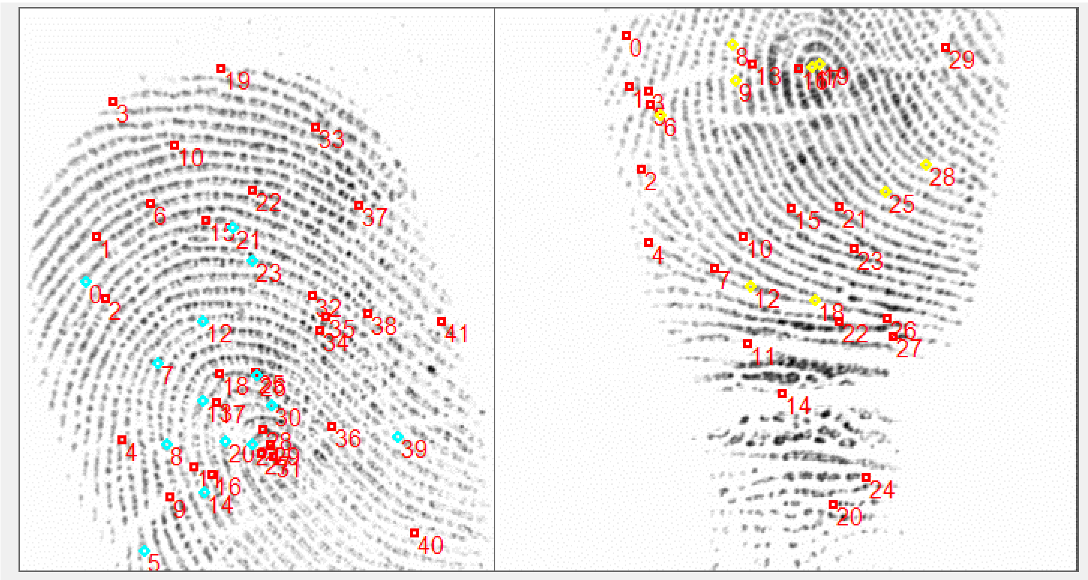


Fig. 4.11: Non-matched pair of mate fingerprint images from FVC DB

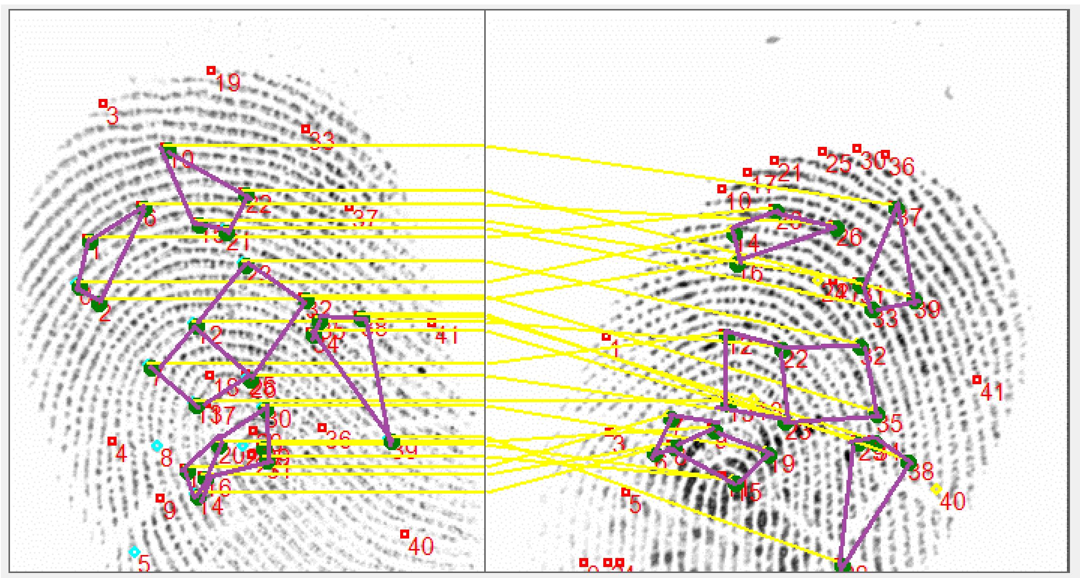


Fig. 4.12: Matched pair of mate fingerprint images from FVC DB

The experiments are conducted on FVC 2004 fingerprint database. The results are compared with M3GL Triples algorithms as shown in Table 4.4 *(* indicates: local nearest neighbors=8, distance threshold=12, global distance threshold =12 and angle* *threshold = 30) (** indicates: local nearest neighbors=12, distance threshold=10, global distance threshold =12 and angle threshold = 30).* The ROC curves for the same experiments are illustrated in Figs. 4.13, 4.14, and 4.15. The proposed fingerprint algorithm is evaluated for two different settings of parameters. One is having values of local nearest neighbors=8, distance threshold=12, global distance threshold =12, and angle threshold = 30. The other parameter are local nearest neighbors=12, distance threshold=10, global distance threshold =12, and angle threshold = 30.

Table 4.4: Equal error rates for the fingerprint matching using triplets and quadruplets on FVC 2004 database

Database	EER(triplets) (%)	EER (quadruplets) (%) *	EER (quadruplets) (%) **
DB1A	22.9	10.05	7.53
DB2A	20.7	10.93	7.87
DB3A	8.9	8.50	6.50
DB4A	24.2	7.79	6.05

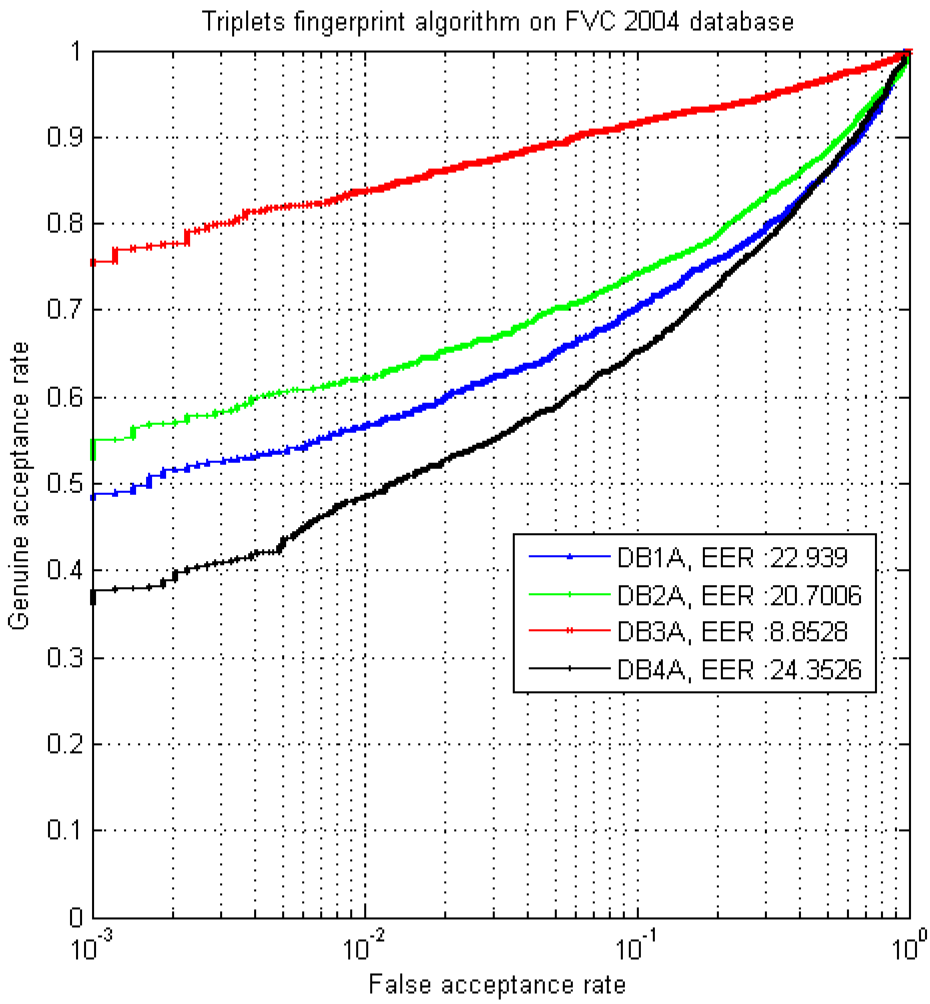


Fig. 4.13: ROC curve for the fingerprint matching using triplets on FVC 2004 database

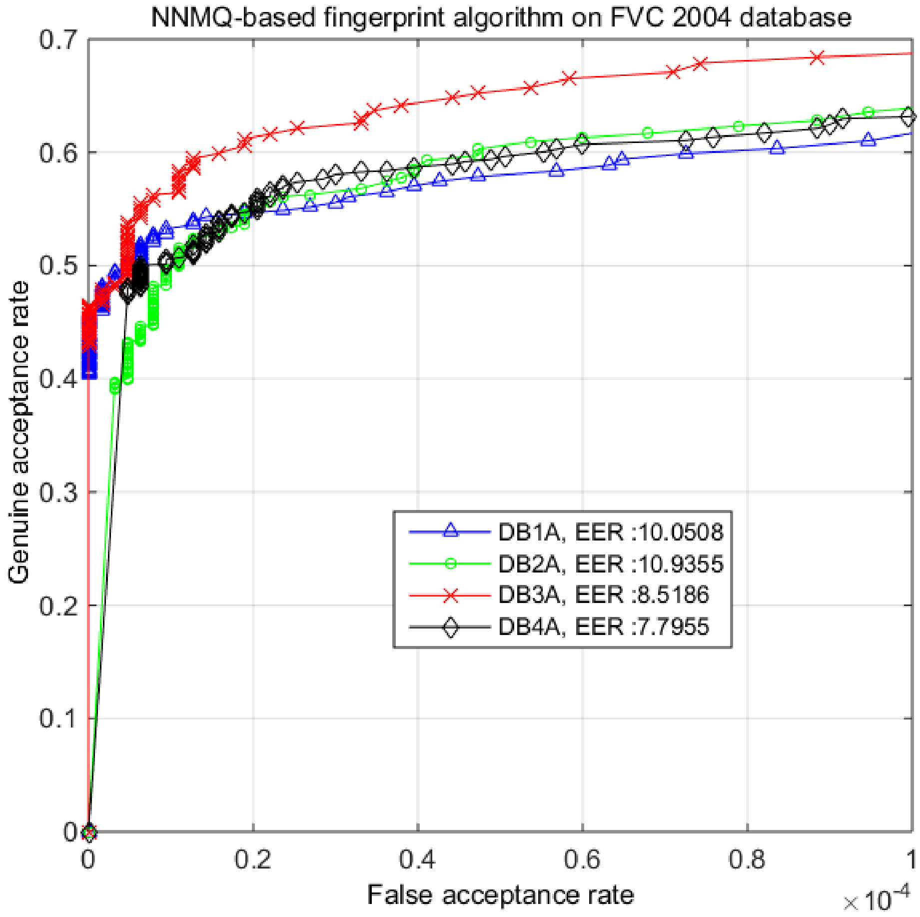


Fig. 4.14: ROC curve for the fingerprint matching using quadruplets on FVC 2004 database (* indicates: local nearest neighbors=8, distance threshold=12, global distance threshold =12, and angle threshold = 30)

The proposed algorithm is compared with the algorithm based on triplets. Fig. 4.13 gives that the EER on FVC 2004 database on DB3A is 8.8528%, where as the proposed algorithm EER on the same database is 6.5024% (shown in Fig. 4.15) with reduced space and time complexities.

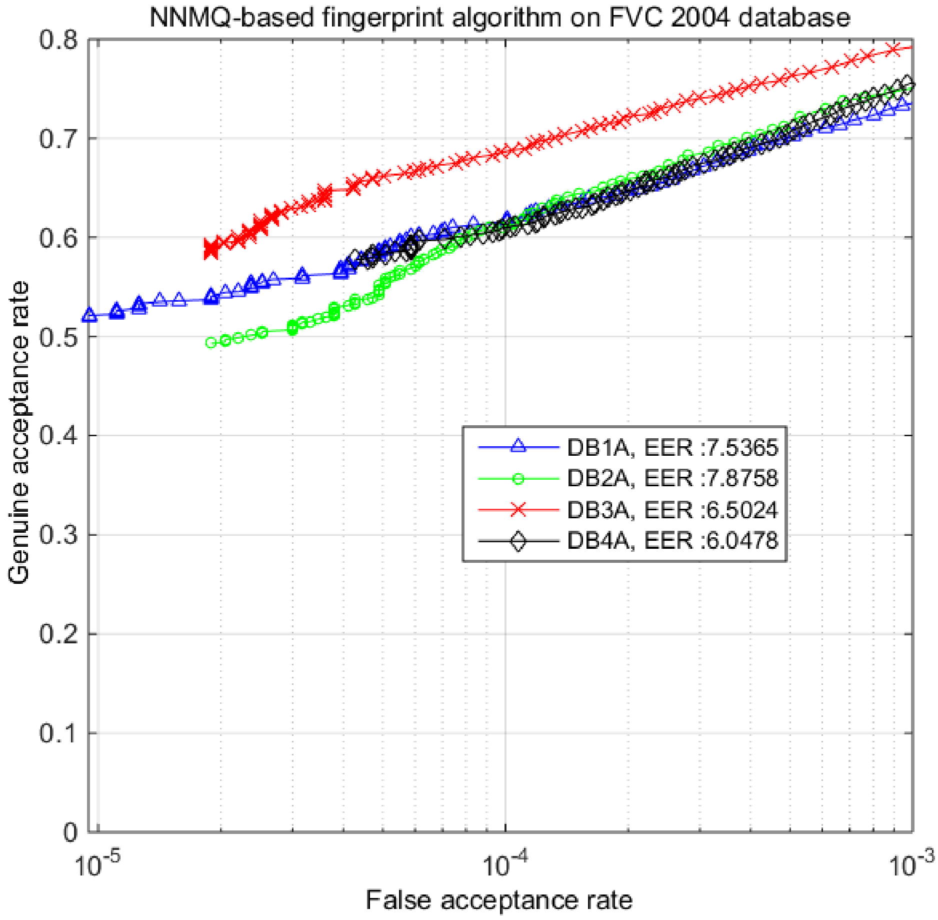


Fig. 4.15: ROC curve for the fingerprint matching using quadruplets on FVC 2004 database (* indicates: local nearest neighbors=12, distance threshold=10, global distance threshold =12, and angle threshold = 30)

Table 4.5 gives space and time complexities of the algorithm on FVC ongoing data sets. It can be observed that the proposed fingerprint matching algorithm outperforms in the space and time complexities when compared to the other algorithms (MntModel, MAJU-VISPRS-FIS-algo, ABVD and MCC(BaseLine)) which were published from academic institutions. This reduced space and time complexities is mainly due to the less minutiae characteristics consider while matching, and also, the quadruplets used for matching.

Table 4.5: Time and space complexity results on FVC ongoing data ISO-matching

Algorithm	Space (KB)	Time (ms)
MntModel	2044	116
MAJU-VISPRS-FIS-algo	8672	21
ABVD	11704	74
MCC(BaseLine)	24076	242
FMIsoMatcher (proposed)	1992	19

Verification experiments are conducted on the standard fingerprint verification benchmark data, FVC ongoing competition. Table 4.6 gives the space and time complexities of fingerprint verification on FVC ongoing data sets. It can be observed that the proposed fingerprint matching algorithm outperforms in the space and time complexity when compared to the other algorithms SourceAFIS (Independent developer), fpcoreII, psmath and HXKJ which were published from companies.

Table 4.6: Time and space complexity results on FVC ongoing data verification

Algorithm	Space (KB)	Time (ms)
SourceAFIS	24216	953
fpcoreII	26308	247
psmath	49784	27
HXKJ(BaseLine)	50732	336
FingerSDK (proposed)	3016	24

4.5 SUMMARY

The majority of existing algorithms are based on fixed radius structure or graph based similarity techniques for matching. These methods are prone to missing of genuine minutiae and presence of impostor minutiae. They also utilize more space for storing fingerprint data. So, we have proposed a new approach for fingerprint matching using

k-nearest and minutiae quadruplets to overcome the above mentioned issues. The proposed fingerprint matching algorithm is evaluated on FVC data sets. The experiments study suggests that the proposed algorithm, achieves comparable performance with existing approaches while using less space and time.

CHAPTER 5

SEMI-AUTOMATED LATENT FINGERPRINT MATCHING USING GLOBAL MINUTIAE MATCHING TECHNIQUE

The issues related to plain fingerprint matching and the proposed approaches to address these issues effectively are discussed in the earlier chapters. In this chapter, we study latent fingerprints (shown in figure 5.1 [106]) which are captured at crime scenes. These latent fingerprints are low quality images with partial and overlapped impressions, there by making them more challenging to recognize. The existing approaches require minutiae points marked manually by forensic experts. To overcome this constraint, we propose a semi-automated feature extraction approach that analyzes the selected region of interest, to detect minutiae points. These minutiae points are in-turn used by a novel global minutiae matching approach that is tolerant to spurious minutiae, for effective fingerprint matching.

This chapter is organized as follows: In Section 5.1, the latent fingerprint extraction from surfaces is described. Section 5.2 covers the existing methods for latent fingerprint recognition. Section 5.3 describes latent fingerprints and feature extraction from latent fingerprint and the proposed semi-automated latent fingerprint matching algorithm. The experimental results is given in section 5.4. Section 5.5 summarizes the study.

5.1 LATENT PRINT PROCESSING

In fingerprint comparisons, the continuity of the ridge flow is vital to the outcome of the comparisons. Smoother surfaces usually deliver better quality impressions, but depending on the specific surface, it is possible to obtain fingerprints from rough or

Fig. 5.1: Latent fingerprint from NIST special database 27 ([106])

textured surfaces.

Evidence types are categorized based on the porosity of the surfaces. Surfaces are generally divided into three types:

- $Porous \ \ surfaces$: These sorts of surfaces retain water and water dissoluble stores in the sweat rapidly after affidavit. Examples: paper, checks, cash, tissue, cigarette butts, cardboard, fabrics, untreated wood, and so on. The extraction of usable latent fingerprints from this surfaces is easier.

- $Non - porous \ \ surfaces$: These types of surfaces do not absorb the sweat. The fingerprint deposits can remain on the surface for a very long time. The extraction of usable latent fingerprints from this surfaces is becomes easier.

- $Semi{-}porous \ \ surfaces$: These sorts of surfaces ingest water and water solvent store in the sweat gradually. Some of the examples are plastics, waxed surfaces, certain sorts of divider paints, papers with a shiny completion, and varnished wood.

5.2 EXISTING MATCHING TECHNIQUES ON FINGERPRINTS

Peng shi et. al. [107] propose a novel fingerprint matching algorithm based on minutiae and global statistical features. In this work, they introduced similarity of global statistical features, which was combined by two statistical quality features of both fingerprints namely, the quality of distribution and the mean ridge width, and proposed a novel similarity measure algorithm based on them. In their algorithm, first they get the raw similarity measure between two minutiae sets. Then the similarity of ridge width between two fingerprints was calculated, and combined with the similarity of minutiae sets. Finally, judge whether the match between two templates belongs to the genuine match or the impostor match by a fuzzy calculation of the quality contrast between both fingerprint images, and complete the matching process by calculating the final similarity measure with the global statistical features.

Soweon Yoon et. al. [108] proposed altered fingerprints: analysis and detection. They considered the problem of fingerprint alteration or obfuscation. Fingerprint obfuscation refers to the deliberate alteration of the fingerprint pattern by an individual for the purpose of masking his identity. The fingerprint image quality assessment software (e.g., NFIQ) cannot always detect altered fingerprints, since the implicit image quality due to alteration may not change significantly. They classify altered fingerprints into three categories based on the changes in ridge pattern due to alteration: 1) Obliteration, 2) Distortion, and 3) Imitation. They proposed an algorithm called automatic detection of altered fingerprints. At a false positive rate of 0.3 percent, the proposed algorithm can correctly detect 66.4 percent of the subjects with altered fingerprints, while 26.5 percent of such subjects are detected by the NFIQ algorithm.

Xinjian Chen et. al. [109] proposed an algorithm for distorted fingerprint matching based on local triangle feature set. They proposed a method for deformed fingerprints matching. A fuzzy feature match (FFM) based on a local triangle feature set to match the deformed fingerprints. The fingerprint is represented by the fuzzy feature set: the local triangle feature set. The similarity between the fuzzy feature set is used to characterize the similarity between fingerprints. A fuzzy similarity measure for two triangles is introduced and extended to construct a similarity vector including the triangle-level similarities for all triangles in two fingerprints. Accordingly, a similarity vector pair is defined to illustrate the similarities between two fingerprints. Finally, the FFM method maps the similarity vector pair to a normalized value which quantifies the overall image to an image similarity within the real interval [0, 1].

Some algorithms combine ridge orientation with minutiae information either at feature level by including ridge orientation information in local minutiae descriptors [110] [111] or at score level by combining scores from minutiae matching and global orientation field matching [111] [112]. Several recent studies on fingerprint matching have focused on the use of local minutiae descriptors [110] [111] [113] [114] [115]. In most of these studies, the initial step consists of using local minutiae descriptors to obtain the alignment between two fingerprints by considering the most similar minutiae pair then a global consolidation step is performed to obtain a better matching performance. The improved latent matching accuracy has been reported in [116] [117] [118] [119] using extended features, which are manually marked for latents. However, marking extended features (orientation field, ridge skeleton, etc.) in poor quality latents is very time-consuming and might be feasible only in rare cases. Thus, some studies have concentrated on latent matching using a reduced amount of manual input, such as manually marked region of interest (ROI) and singular points [120] [121]. However, only a small portion of latents can be correctly identified using this approach. Hence, our proposed matcher takes manually marked minutiae as input and therefore, it is consistent with existing practice. There have also been some studies on fusion of multiple matchers [122] or multiple latent prints [6]. NIST has been conducting a multiphase project on "evaluation of latent finger-print technologies (ELFT)" to evaluate latent feature extraction and matching techniques [123].

The noise and low quality of latent fingerprints make the automatic extraction of minutiae points a challenging task. In this work, a semi-automated latent fingerprint matching approach using global minutiae features on ISO-19794-2 fingerprint templates is proposed. We use global and local adaptive binarization techniques to minimize the noise in the extracted features. As the minutiae detected automatically from latent fingerprints are prone to be spurious, we propose a global minutiae matching technique that is tolerant to noise.

5.3 LATENT FINGERPRINT RECOGNITION

Most of the recognition algorithms for fingerprint comparison are based on minutiae matching. As shown in figure 5.2, there are three different types of finger acquisition, namely, rolled fingerprints, plain fingerprints, and latent fingerprints. The rolled fingerprints can be collected by placing the fingerprint on the fingerprint sensor surface and moving it from nail to nail. The plain fingerprints can be captured by simply placing the fingerprint on the sensor surface. The latent fingerprints can be collected from the scene of crime as part of the forensic analysis. It is difficult to extract the genuine minutia automatically from the latent fingerprints because of low fingerprint quality and less area of interest on the fingerprint. The ridge structures are not always well defined because of the poor-quality latent fingerprint images and, hence, there may be chances of detecting the spurious minutiae. Even though the fingerprint recognition technology is more advanced, there is no automated latent fingerprint technology in the biometric domain.

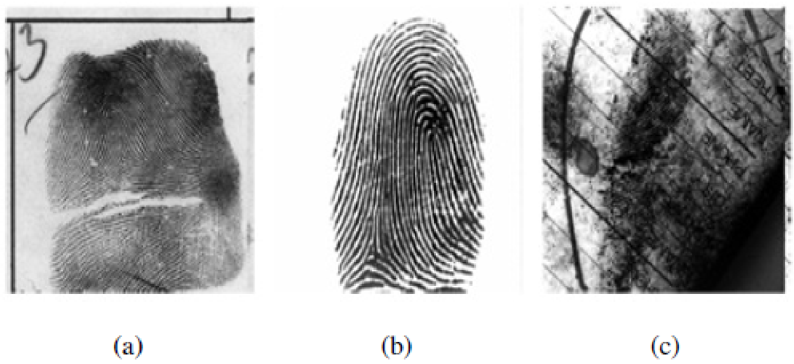


Fig. 5.2: (a) rolled fingerprint (b) plain fingerprint (c) latent fingerprint

5.3.1 Latent fingerprint feature extraction

A latent fingerprint image consists more noise when compared to the plain fingerprints due to the acquisition and environmental conditions at the crime scene. The image enhancement is introduced as a preprocessing step to reduce the noise and to enhance the definition of ridges against valleys. There are two adaptive preprocessing operations involved, namely, matched filter and adaptive thresholding. The steps involved in fingerprint enhancement are illustrated in figure 5.3.

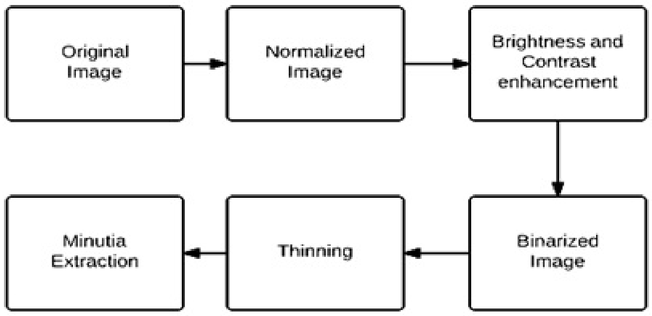


Fig. 5.3: Latent fingerprint feature extraction steps

Each step in fingerprint enhancement is explained in detail in the following sections. Even though there may be discontinuities in particular ridges, one can always look at a small, local area of ridges and determine their flow using redundancy of parallel ridges. The redundancy of information is used in the adaptive matched filter, which is applied to every pixel in the fingerprint image. The filter is applied based on the local orientation of the ridges around each pixel, to enhance ridges orientation in the same direction of the same locality. The bridge type of ridge information can be eliminated by using the matched filter. The ridges can be extracted after the fingerprint image is enhanced with noise removal process. The binarization operation takes as input a gray scale image and returns a binary image as output. The image is reduced in intensity levels from the original 256 (8-bit pixels) to 2 (1-bit pixels). The difficulty in performing binarization is that all the fingerprint images do not have the same contrast characteristics, so a single intensity threshold cannot be chosen. Furthermore, contrast may vary within a single image, for instance if the finger is pressed more firmly at the center. Therefore, a common image processing tool is used, called local adaptive thresholding. This operation determines thresholds adaptively to the local image intensities. The results of the binarization of image and the thinning operation are shown in figure 5.4.

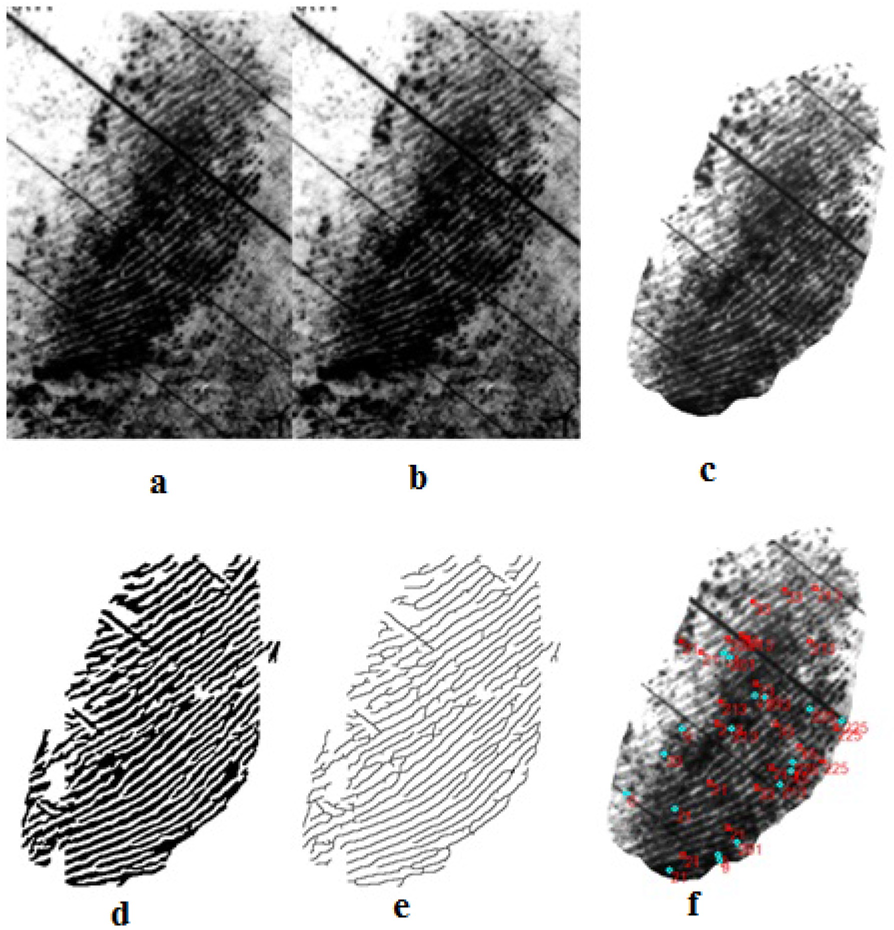


Fig. 5.4: Latent fingerprint feature extraction (a) original image (b) normalised image (c) contrast enhanced image (d) binarized image (e) thinned image (e) minutiae interpolated

5.3.2 Semi-automated latent fingerprint matching

The proposed latent fingerprint matching algorithm uses ISO/IEC 19794-2 fingerprint templates [124]. The fingerprint template consists of the information; coordinates of x-y , direction, type and quality of each minutia. Each edge consists of the information like the edge distance and directional difference between minutiae. The proposed algorithm is of rotation and translation invariant as the algorithm is designed to accept certain deviations in rotation and translation. The following are the steps involved in the global and local minutia matching algorithm that are summarized in Algorithm 3.

Algorithm 3 Global minutiae matching (GMM) algorithm for latent fingerprints:

---

1. Input probe and gallery ISO/IEC 19794-2 templates.
2. Unpack the the template information x and y coordinates, and direction
3. Compute the minutiae edge pair information with all neighbor minutiae.
4. Sort the nearest minutiae using Euclidean distance.
5. Validate the matched minutia pairs with all the matched pairs to remove false matched minutia pairs.
6. Compute the matching score.

5.4 EXPERIMENTAL RESULTS

The experimental results of latent fingerprint impression acknowledgment are displayed in lights out mode. The standard NIST special database 27 [125] is utilized for the tests which contains latent fingerprints and their relating rolled fingerprint mates. There are 258 latent cases, every case incorporates the idle picture and the relating ten print picture. The database is separated into three categories LF-1, LF-2, and LF-3, where the unique finger impression qualities are great, terrible and revolting, individually. There are 88 inert prints in LF-1 bunch, 85 inactive prints in LF-2 bunch and 85 idle prints in LF-3 bunch in SD27 database. Every picture is of size 800 × 768 pixels and put away in an uncompressed position. All the pictures are arranged utilizing the ANSI/NIST-ITL 1-2000 standard and Type-1, Type-13, and Type-14 records. The ISO/IEC 19794-2 layouts are produced from idle and moved fingerprints and submitted for coordinating. The inert prints were coordinated against the plain prints of 1758 pictures which are gathered utilizing three diverse live-scanners (Biomini, Cogent and Upek) and the current moved fingerprints from the SD27 database. The plain unique mark information comprises of all the 10 fingerprints of 30 subjects caught at 5 distinctive occurrences.

Table 5.1 gives the matching performance of latent fingerprints from NIST SD27 database. It is observed that the matching accuracy is better in the group of LF-1 latent fingerprints where 60% of the cases are identified in top 10 of search results, 30% of the cases are identified in top 100 search results and around 10% are not identified. Similarly, in LF-2, latent fingerprints are identified around 40% in top 10 search results, 30% in top 100 search results; and the remaining cases are not identified. LF-3 latent fingerprints around 70% are not identified. It is observed that the matching performance for LF-1 group quality latents is significantly improved when compared with the latent fingerprints belonging to the other two groups LF-2 and LF-3. The performance degradation with LF-2, and LF3 is mainly due to very poor to ugly quality of latent fingerprints.

Table 5.1: Performance (%) of latent fingerprint matching

Latent-Group	Top 10	Top 100	Not in Top 100
LF-1 (Good)	60	30	10
LF-2 (Bad)	40	30	30
LF-3 (Ugly)	10	20	70

It is observed that the rank-1 identification rate for all the latents improved to 79% (LF-1 (87%), LF-2 (78%) and LF-3 (72%)) after the latent fingerprint enhancements using the semi-automated latent fingerprint identification system. The results are compared with the existing method proposed by Anil K Jain et. al. [41] and observed that the improvement in rank-1 identification rate as shown in Table 5.2 with the assumption that there may not be any significant difference in the identification rate even if 1758 images are added to SD27 data set. The improvement in performance is because the global minutiae matching is able to take care of missing of genuine and spurious minutiae.

Table 5.2: Comparison of the performance (%) of rank-1 fingerprint identification

Latent-Group	Anil K Jain et. al.	Proposed method
LF-1 (Good)	83	87
LF-2 (Bad)	74	78
LF-3 (Ugly)	65	72

5.5 SUMMARY

In this chapter, a semi-automated latent fingerprint recognition algorithm is proposed using standard ISO/IEC 19794-2 templates. The proposed algorithm reduces the manual intervention of the fingerprint experts in identifying the suspects. The experimental study conducted on NIST SD-27 database suggests that the algorithm achieves better results for good quality latent fingerprints (LF-1) when compared to the very poor quality latent fingerprints (LF-3), as the automatically detected minutiae in poor quality latent prints are not usable for automatic recognition.

CHAPTER 6

HIGH RESOLUTION PALMPRINT RECOGNITION USING MINUTIAE QUADRUPLETS

Earlier chapters focused on challenges and approaches for recognition of plain and latent fingerprints. In this chapter, we study another biometric trait called palmprint, that shares similar methods for feature extraction and matching with fingerprint recognition. However, there is a performance degradation with palmprint biometrics due to the difficulty in identifying genuine minutia points from regions with highly distorted ridge information. As the palmprint images are 20 times bigger in size compared to fingerprints, the time taken for storing and matching them is also high. The applications of handprints can be broadly classified into the once using low quality images (like for time & attendance) and high resolution images like forensic applications. This work considers palmprint recognition using high resolution images, which is an emerging area of research. Due to the large size of high resolution palmprint images, there is a necessity of algorithms with less memory footprint and low computation cost. In this chapter, we will focus on recognising palmprints captured at a high resolution (500dpi). We propose an efficient palmprint matching algorithm using nearest neighbor minutiae quadruplets.

The contents are organized as follows: Section 6.1, gives an introduction to palmprints. Section 6.2 discusses the existing palmprint recognition methods. In Section 6.3, we describe the proposed method for palmprint recognition. Section 6.4 discusses experiments on standard data sets from FVC and THUPALMLAB, and the performance of the recognition system. Section 6.5 summarizes the study.

6.1 INTRODUCTION

Due to the growing demand of human identification for many ID services, biometrics has become more attracting research area. While the fingerprint recognition system is more convenient and accurate, palmprints can be considered as a variant of fingerprints which shares the similar feature extraction and matching methodology. The palm consists of friction ridges and flexion creases as main features. Due to the folding of palm, flexion creases is formed. The palmprint is having three regions, namely, hypothenar, thenar, and interdigital (see Fig. 6.1).

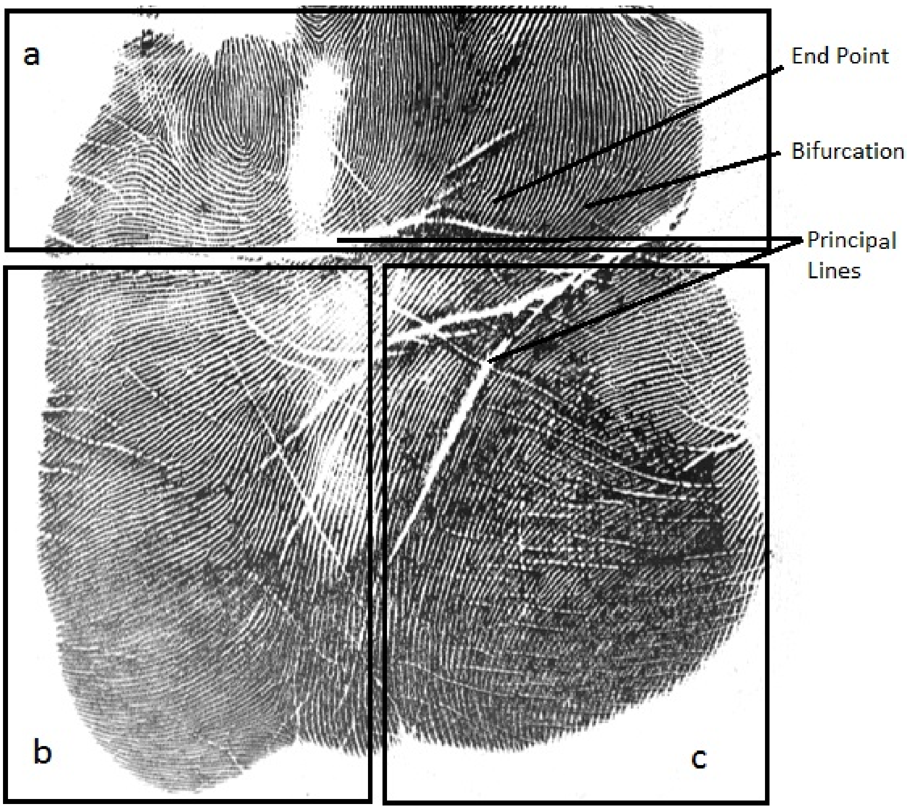


Fig. 6.1: Palmprint Image (a) Interdigital (b) Hypothenar (c) Thenar

In many instances, examination of hand prints like fingerprint and palmprint was the method of differentiating illiterate people from one another as they are not able to write. The first known automated palmprint identification system (APIS) [126] developed to support palmprint identification is built by a Hungarian company. There are mainly two different approaches in palmprint matching on high resolution palmprints, namely, minutiae based [87] and ridge feature-based [88]. The minutiae based palmprint matching methods find number of minutiae matches between the input palmprint (probe) and the enrolled palmprint (gallery). This is the most popular and widely used approach. In ridge feature-based palmprint matching, features of the palmprint ridge pattern like local ridge orientation, frequency, and shape are extracted for comparison. These features may be more reliable for comparison in palmprint of low-quality images than minutiae features. The palmprint matching algorithm is correct when there are genuine matches (true accepts) and genuine rejects (true non-matches). The matching is wrong when there are impostor matches (false accepts) and impostor non-matches (false rejects).

6.2 RELATED WORK

Palmprint recognition research mainly concentrates on low-resolution palmprint images that are captured through low cost cameras [127] [128] [129] [130] [131]. These images are usually captured in a contactless way, the quality is very low. With such low quality, matching will be based on minor and major creases, as the ridges can not be observed. In [132] [133], researchers tried to explicitly extract and match major creases. In [134], Jain and Feng et al. proposed a palmprint recognition based on minutiae by segmenting the palmprint into multiple sub-regions to achieve the acceptable accuracy. In [135], Dai and Zhou et al. proposed a multi-feature based palmprint recognition system, where multiple features including orientation field, density map, major creases, and minutia points are extracted to get higher accuracy. There are a few problems in large-scale palmprint applications such as skin distortion, diversity of different palm regions, and computational complexity.

The existing minutiae based palmprint techniques depend on segmentation of palmprints, thereby increasing its time complexity. In this work, a minutiae based matching approach without segmenting the palmprints is proposed to improve the overall efficiency of the matching process.

6.3 PALMPRINT RECOGNITION

Palmprint recognition is computationally expensive as the high resolution palmprint image is bigger in size. The speed and accuracy of the palmprint recognition is very less, even though it is sharing the same parameters used for fingerprint recognition. The typical high resolution palmprint is 16 to 20 times bigger in size than fingerprint, that is why the palmprint recognition is less accurate and very slow in recognition.

6.3.1 Palmprint feature extraction

The extraction of the robust palmprint features is a challenging problem due to the noise and creases present in the palmprint. The palmprint image quality is low due to the wide creases (principal lines) present and more number of thin creases. The size of palmprint image is very large. The full fingerprint at 500 dpi is about 256 kilobyte, where as a full palmprint at 500 dpi is about 4 megapixels. A palmprint feature extraction that is robust enough to deal with the average quality of palmprint is not easy to design.

Feature extraction is the very important phase of the biometric recognition. The accuracy of matching algorithm depends on the quality of the features extracted. Figure 6.2 shows the various phases involved in the feature extraction of palmprint and the details of each phase is as follows:

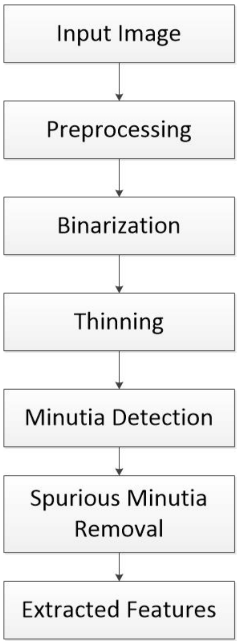


Fig. 6.2: Variuos phases of feature extraction

1. *Smoothing*: It is an image processing operation to reduce the noise of the image. We have used Gaussian smoothing function to reduce the noise of the image. The Gaussian smoothing is by

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}, \tag{6.1}$$

   where σ is the standard deviation of the Gaussian distribution, x is the distance from the origin in the horizontal axis, and y is the distance from the origin in the vertical axis.

2. *Binarization*: In this step, the image is converted in to complete black and white pixels from gray scale. Local and global adaptive binarization is the process that combines local mean intensity as well as global mean intensity information to binarize the fingerprint image. This combination works very well for the noisy finger prints that are captured on the fingerprint scanners where the previous fingerprints residue is left as a ghost image on the surface of the fingerprint scanner. The global mean intensity is the sum of all the pixel in-

tensity values divided with the total number pixels present in the image. The global binarization uses the global mean intensity as the threshold to binarize the fingerprint image, whereas the local adaptive binarization uses the mean intensity of each 8×8 block from the fingerprint image and binarizes the particular block of corresponding local mean intensity value. The proposed binarization combines both the global binarization as well as local adaptive binarization, to remove the spurious minutiae that are formed due to noise and ghost images present in the palmprint. The proposed combination of global and adaptive binarization removes the spurious minutia that are formed due to the ghost images and also improves the accuracy of palmprint feature extraction by removing the noise and ghost images present in the background.

3. *Thinning*: Binarized image ridges are converted to one pixel thickness, which are useful for extraction of minutiae. This operation is necessary in order to simplify the subsequent structural analysis of the image for feature extraction. We used a K3M Thinning algorithm [136] to do thinning.

4. *Minutiae Extraction*: Minutiae extraction is done on thinned image. The minutiae are extracted by scanning the local neighborhood of each ridge pixel in the image using a 3×3 window shown in figure 6.3. The most commonly employed method of minutiae extraction is the crossing number(CN) method. The crossing number(CN) is defined as half the sum of the difference between pairs of adjacent pixels in the eight neighborhoods, is as shown in equation 6.2. Using the properties of the crossing number, the ridge pixel can then be classified into a ridge ending, bifurcation, and non-minutiae point.

P4	P3	P2
P5	P	P1
P6	P7	P8

Fig. 6.3: A 3×3 mask for pixels

The value of the crossing number (CN) is computed as

$$CN = 0.5 \times \sum_{n=1}^{8} |P_n - P_{n+1}|, \tag{6.2}$$

where p is the pixel of interest, p_n is the neighboring pixel, and $p_9 = p_1$

5. *Spurious Minutiae Removal*: This is the final stage of feature extraction where the spurious minutiae due to ridge cuts, border minutiae, bridges, lakes are removed. To remove the border minutiae, the image is segmented to foreground and background regions using the quality map. The minutiae which are nearer to image background are removed.

The figure 6.4 shows the output images of palmprint corresponding to various phases of feature extraction.

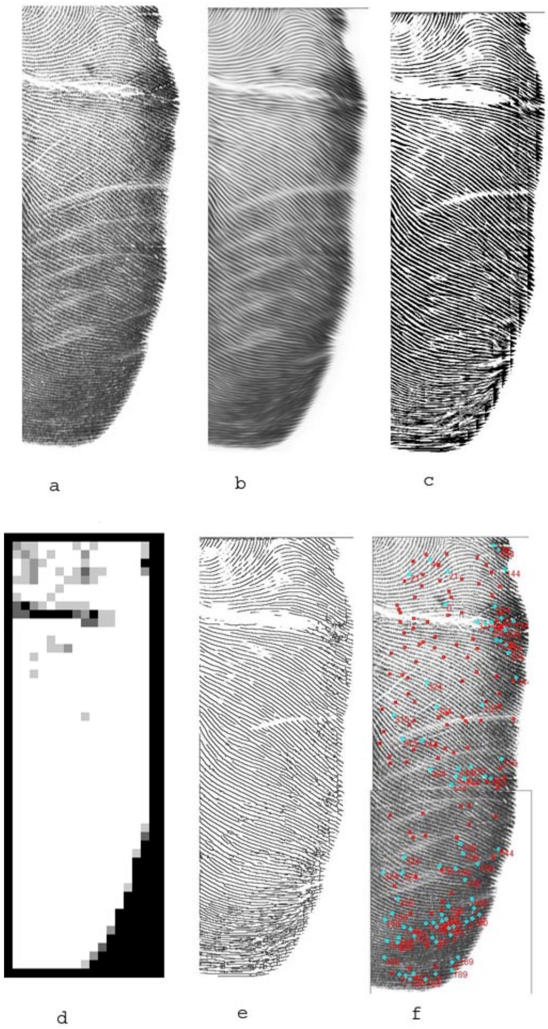


Fig. 6.4: Various phases of palmprint feature extraction: (a) Original image (b) Smoothed image (c) Binarized image (d) Quality map of image (e) Thinned image (f) Minutiae interpolation

6.3.2 k-Nearest neighbor matching algorithm

This k-nearest neighbor matching algorithm finds the probable matching minutiae mates from query template and probe templates. The feature vectors corresponding to the query template and probe template are denotes as G and P, respectively. The proposed minutiae-based method considers mainly three features from each minutia m $= x$, y, θ, where x, y is the location and θ is the direction. Let $G = m_1, m_2, ...m_m, m_i =$

$x_i, y_i, \theta_i, i = 1, ..., m$ and $P = m_1, m_2, ...m_n, m_i = x_i, y_i, \theta_i, i = 1, ..., n$, where m and n denote the number of minutiae in gallery and probe template, respectively. The Euclidean distance between minutiae a and b is given as

$$Dist_{ab} = \sqrt{(x_a - x_b)^2 - (y_a - y_b)^2}, \tag{6.3}$$

where $Dist_{ab}$ is Euclidean distance between minutiae points a and b, x_a is co-ordinate x of minutiae point a, y_a is co-ordinate y of minutiae point a, x_b is co-ordinate x of minutiae point b, and y_b is co-ordinate y of minutiae point b.

The direction difference between minutiae a and b is defined as

$$Dir_{ab} = \arctan \frac{(y_a - y_b)}{(x_a - x_b)}, \tag{6.4}$$

where Dir_{ab} is direction difference between minutiae points a and b.The Algorithm 4 finds the similar mates from query template and probe template using k-nearest neighbor local minutia matching techniques.

6.3.3 Computing match score using quadruplets

This step considers short listed minutiae from k-nearest neighbor stage. The shortlisted minutiae pairs from k-nearest neighbor minutiae is considered as reference pair for finding quadruplet. The Algorithm 5 describes the quadruplet matching algorithm.

6.4 EXPERIMENTAL SETUP AND RESULTS

The experiments are conducted on the standard palmprint benchmark data sets FVC ongoing competition test data [103] and Tsinghua university [137] [138] [139]. The test data consists of 10 people, 1 palm of 8 instances. The Tsinghua university data set consists of 80 people, 2 palms of 8 instances. These experiments were carried out on Intel core i3 machine with 4 GB ram and 1.70 GHz processor. Figures 6.5 and 6.6 show the ROC curves over the standard databases FVC Ongoing and Tsinghua THUPALMLAB data sets.

Algorithm 4 k-nearest neighbor matching algorithm

1. Input query and reference ISO templates.

2. Get the query and reference templates X, Y, direction, type, and quality.

3. Compute the edge pair information for each minutia to all other minutia.

4. Sort the edge pair information using Euclidean distance.

5. Find the mates for each minutia in query and probe template using k-nearest neighbors (k= 5,6,7 and 8), using Euclidean distance and direction difference.

6. Let P and Q be the fingerprint minutia of probe and gallery images, respectively, and R and S be the minutia edge pair information. Let M be the set of local minutia pairs which are matched from query and probe template.

7. Sort minutia pair information in query and probe in ascending order using Euclidean distance.

8. Find the similarity from R to S using nearest k-neighbors (5,6,7 and 8) with distance and direction parameters.

Algorithm 5 Quadruplet matching algorithm

1. Input the minutiae that are shortlisted from $k - NN$
2. Find the similarity from P to G using distance and direction parameters to three minutiae points.
3. Repeat the above step for all other minutiae from set p.
4. Compute the score from the probable minutiae quadruplets

Table 6.1 shows the databases with number of persons, genuine, and impostor attempts. Table 6.2 shows that the standard databases, nearest neighbors considered, and equal error rate(EER). The accuracy of the algorithm is good when nearest neighbors considered 6 with the two databases. The $DistThr$ is 12, $DirDiff$ is 30 and $RelDiff$ is 30 considered in all the experiments. Table 6.3 shows that the standard databases, nearest neighbors considered, space, and time taken for each verification.

Table 6.1: Databases

Data set	No. of Persons	Instances	Genuine	Impostor
FVC Ongoing	10	8	280	2880
THUPALMLAB	80	8	4480	20000

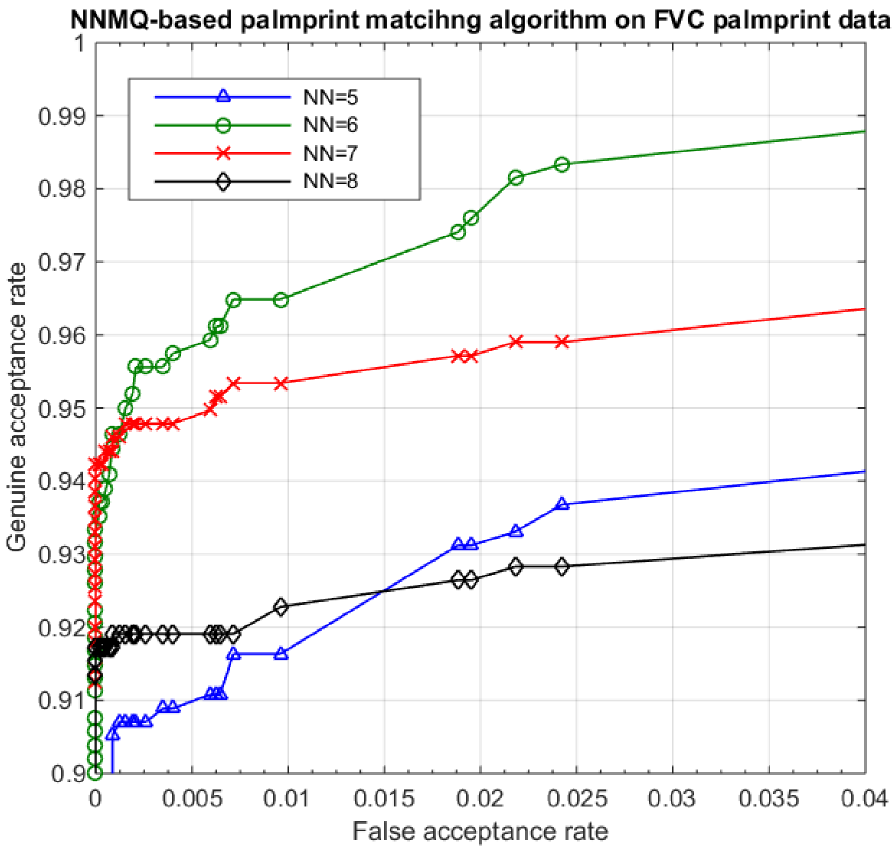


Fig. 6.5: ROC on standard FVC test data

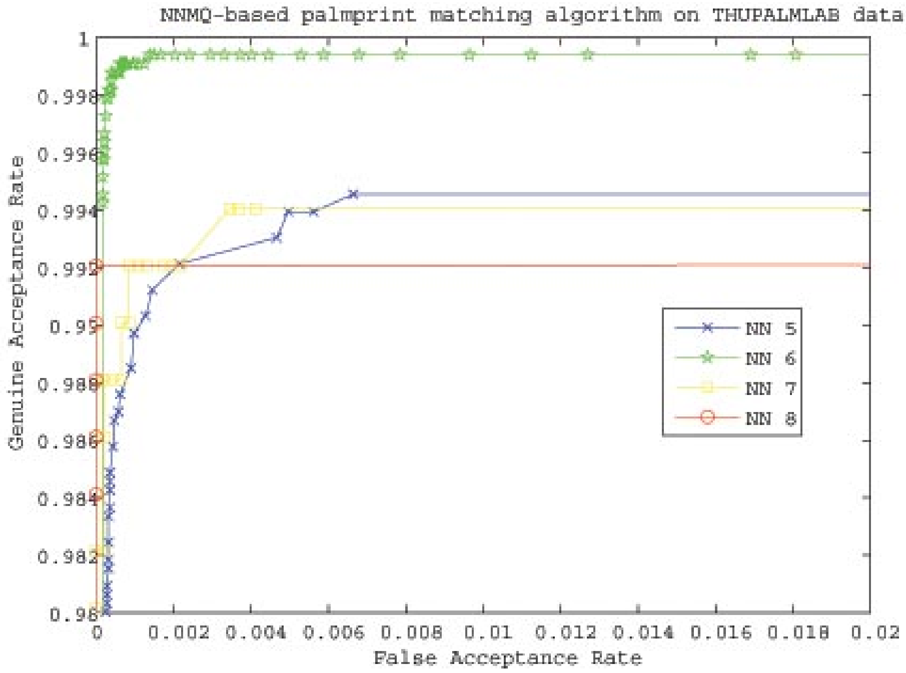


Fig. 6.6: ROC on Tsinghua THUPALMLAB data

It can be clearly observed from the Table 6.2 that on both THUPALMLAB and FVC data sets, the lowest EER is achieved when 6 nearest neighbors are considered for matching.

Table 6.2: EER on FVC and THUPALMLAB data sets

# NNs	EER (%) on FVC Ongoing	EER (%) on THUPALMLAB
5	4.56	0.56
6	3.87	0.12
7	4.30	0.69
8	5.08	0.83

Table 6.3: The amount of space and time taken on FVC and THUPALMLAB data sets

# of NNs	Space (KB)	Time (ms)	Space (KB)	Time (ms)
	FVC Ongoing		THUPALAMLAB	
5	32524	2089	32480	2535
6	32572	2347	32564	4017
7	32488	2388	32512	4435
8	32536	2711	32504	5154

The proposed algorithm achieved 0.12 percent of EER on THUPALMLAB data set, whereas, the EER of [134] [135] on THUPALMLAB data set are 7 percent and 4.8 percent, respectively [135] given in Table 6.4. It can be observed that the proposed out performs existing algorithms with the help proposed new technique.

Table 6.4: EER of algorithms on THUPALMLAB data set

	Proposed	**Jain et. al.**	**Dai et. al.**
EER (%)	0.12	7	4.8

6.5 SUMMARY

The proposed palmprint matching algorithm uses the new representation of minutiae points (quadruplets) and matching is done without segmenting the palmprint. The experiments suggest that the proposed matching algorithm achieves better accuracy over existing approaches on standard data sets. The proposed algorithm on FVC palm test data have achieved EER 3.87 % and on THUPALMLAB data set achieved EER of 0.12 %.

CHAPTER 7

BIOMETRICS IN LARGE SCALE e-GOVERNANCE APPLICATIONS AND BEST PRACTISES

In the previous chapters, we discussed approaches to cross-sensor fingerprint recognition, minimize resource (space and time) utilization for recognizing plain fingerprints, semi-automated latent fingerprint recognition, and palmprint matching with high-resolution images. This chapter focuses on extending these approaches further, for real-time authentication in large-scale applications. The enhanced approaches are demonstrated for two large-scale biometric applications in the fields of civilian and academia, which can be seamlessly extended to other application domains. In this chapter, we utilize the algorithms proposed in this thesis for two real-life applications using hand-held terminals in the fields of e-governance and academia. The first application uses fingerprint authentication for public distribution system (PDS) using point of sale (PoS) device. The public distribution system finds the genuine beneficiaries with the help of electronic fingerprint authentication system that uses Aadhaar central identification repository (CIDR). The second application uses fingerprint authentication to automate the attendance system for students using hand-held readers. Many educational institutions are moving towards automated biometric based attendance system. So, we propose a method to automate student attendance using IP-based fingerprint reader.

The current PDS system is manual, using paper based records that are prone to errors, either intentionally or unintentionally. So, we propose a fingerprint based authentication system that avoids these errors to avail the benefits from FP-shop, using Aadhar authentication platform.

This chapter is organized as follows: the large-scale fingerprint authentication applications considered in this study are explained in Section 7.1. Section 7.2 presents hand-held fingerprint units used for fingerprint authentication. In section 7.3, the implementation of the system is explained. Section 7.4, contains the analysis of experimental results. In section 7.5, summary is provided.

7.1 LARGE-SCALE FINGERPRINT AUTHENTICATION APPLICATIONS

In this section two large scale application related to civilian and academia is presented briefly.

7.1.1 Aadhaar authentication

Aadhaar project is implemented by UIDAI (Unique Identification Authority of India) [140]. The main objective of Aadhaar project is to provide an unique number based on the person's biometrics such as fingerprints, iris, and face. As part of the enrollment phase, 10 fingerprints, 2 irises, and one face photograph of each person are collected and stored in a central identification repository (CIDR). This Aadhaar number is the single source of identity verification. By providing a clear proof of identity, Aadhaar will facilitate entry for the residents to avail the welfare schemes and services such as PDS provided by the government. There are few existing public utility systems which are implemented based on smart cards in the countries Austria , Germany , Taiwan , Italy, and Mexico [141]. Aadhaar authentication is an on-line process of submitting Aadhaar number along with other attributes, including biometrics to the CIDR. Aadhaar authentication provides several ways in which a resident can authenticate themselves using the system. At a high level, authentication can be demographic authentication and/or biometric authentication. During the authentication transaction, the residents record is first selected using the Aadhaar number and then the demographic or biometric inputs are matched against the stored data provided by the resident during enrollment or update process. The fingerprints in the input are matched against all stored 10 fingerprints.

7.1.2 Students attendance in academia

Now a days, there is a growing demand for biometrics in academic institutions for students attendance. The existing biometric time and attendance system is not convenient to utilize for students attendance. The issues involved in student time and attendance system are as follows: 1) In general, the fingerprint readers in the time and attendance system are mounted to a wall, which is not flexible for taking students attendance and also it is a time consuming process. 2) Allotting class timings in device-level is a difficult task because some classes will be at flexible timings.

7.2 HAND-HELD FINGERPRINT TERMINALS

There are two different types of hand-held fingerprint terminals which are used in the proposed methods of fingerprint authentication or verification. One is the point of sale (PoS) device and the other is the IP-based fingerprint reader.

7.2.1 Point of sale device

The point of sale (PoS) device consists of the display module, communication module, biometric module, and printer. The communication modules are GPRS modem and Ethernet connection. The PoS device consists of the UID compatible application interface for generating the request which is compatible with UID/Aadhaar authentication. The device will be placed at the fair price shop (FP shop) with the dealer. The device is locked with particular FP shop dealer to make sure the device is operated by dealer only with his UID authentication. The PoS based on-line authentication systems have lot of advantages over traditional smart card authentication systems[10].

7.2.2 IP-based fingerprint reader

The proposed implementation of portable time and attendance system uses Suprema BioLiteNet [142] fingerprint reader. This device has the features like LAN connectivity through which data can be transferred from device to server and vice versa. Each device can store up to 3000 persons biometric fingerprint templates of two fingers. The device can store the logs of student attendance is around 60000.

The details of the model used for PDS system and student time & attendance system are described below.

7.3 IMPLEMENTATION MODEL

The fingerprint authentication work flow for the public distribution system and student time and attendance is explained in the following subsections.

7.3.1 Aadhaar authentication system

The intention of Aadhaar authentication in welfare schemes is to reduce the fraud involved with the manual system and to bring the transparency. The Aadhar authentication system implementation is as follows:

1. The residents provide Aadhaar number, necessary demographic, and biometric details at PoS terminals to an operator.
2. Each device is installed with the Aadhaar authentication-enabled software which packages the input parameters. The package will be encrypted and transmitted to the authentication server using a broadband/mobile network.
3. Authentication server validates the package and adds necessary headers (license key, transaction id, etc.), and passes the request to the central server (UIDAI CIDR).
4. Aadhaar authentication server returns a yes/no based on the matching score of the input parameters.

5. The operator proceeds with the transaction based on the response at the PoS device.

Following are the advantages of using PoS based biometric authentication system:

1. The services are provided to the beneficiaries in a fast and efficient manner.
2. The commodities will be allocated to the FP shop based on the real time closing balances.
3. The accountability and transparency is increased at FP-shop level.
4. The eligible beneficiaries can get the commodities without wastage.

The program requires UID number as primary key for distribution of commodities. There is a secondary authentication method using mobile numbers for the residents who are not having the Aadhaar numbers. The PoS terminal generates a one time password (OTP) and will be verified using the SMS received in the mobile. If the user does not have UID as well as mobile number, a Government supervisor will authenticate on behalf of the beneficiary.

7.3.2 Student time and attendance

Student time and attendance system is intended to avoid the paper work and to bring the transparency. The fingerprint authentication implementation for the student time and attendance system as follows:

1. The details of students, faculty and courses are collected.
2. In the enrollment phase, the biometric fingerprint templates are collected from faculty members and students. Each person is assigned with a biometric ID which is unique.
3. Once the enrollments are completed, each faculty is allotted with a BioLiteNet fingerprint device. For example, a faculty member dealing with three courses in

a semester, the two fingerprints (left index and right index) of students who are registered for those courses are stored in that particular device. For the entire semester, the device is dedicated to that faculty member.

4. Each course is assigned a biometric ID and the authorized person for that course. Only the authorized person can verify the course based on course-biometric ID. The authorized person may be faculty member or teaching assistant of that particular course.
5. As and when the faculty member takes a class, he/his teaching assistant needs to carry the device. Before the class starts, faculty member or his teaching assistant need to authenticate the course by entering the course-biometric ID and his fingerprint. This is a mandatory task which will be used to track the course wise attendance easily from the device at a later point of time.
6. Once course authentication is over, the device will be passed on to each student for their finger authentication, which stores the attendance status of each student for that particular course.
7. At regular intervals of time (may be weekly or monthly), the faculty or teaching assistant is responsible for syncing the data to the server from anywhere in the institutes LAN network.
8. At the server side, all these details will be segregated based on course-registration details.

7.4 PROGRAM ANALYSIS AND EXPERIMENTAL RESULTS

The analysis and experimental results of the Aadhaar authentication and student time & attendance is discussed below.

7.4.1 Aadhaar authentication system

The proof of concept was implemented in 100 fair price (FP) shops in Andhra Pradesh, India [143] [144]. As part of this analysis, rural, urban, and hamlet areas are chosen. Nearly, 85 percent of the beneficiaries have the UID numbers and remaining 15 percent beneficiaries have EID (Enrollment Id) numbers. The beneficiaries who have UID numbers are authenticated using fingerprints captured from PoS terminal. The beneficiaries with EID numbers are authenticated using (one time password) OTP or authorized village servants UID on behalf of the beneficiary. Initially, in the first month of implementation, 97 percent of the beneficiaries are authenticated with their fingerprints and the remaining 3 percent of the beneficiaries who are not mapped their UIDs at the central server. In the second month, 99 percent of the beneficiaries authenticated with their fingerprints and rest of the beneficiaries not able to authenticate due to the bad quality fingerprints. The authentication accuracy is improved by fusing the matching scores of two fingerprints. Initially, the average number of authentications for each person was around two attempts and later it is reduced to 1.3 attempts using the method of best finger detection.

The 'best finger detection 'method captures the ten fingerprints of the beneficiary and sends the data in the form of UID compliant packet to the central server. It processes the request and gives the response of best fingers of the beneficiary on the rank scale of 1 to 10. If the fingerprints are not matched with the existing fingerprint data in the central server, the best finger detection method prompts the message recapture fingerprints again. The implementations have weed out nearly 5 percent of the bogus cards and showed nearly 20 percent of savings to government. The tests have been conducted on nearly 70000 families. Each family consists of approximately 4 persons and 85 percent of these families are having valid UID numbers. The transaction trend is shown figure 7.1, for 9 months starting from September - 2012 to May - 2013. The first two months, this program is implemented in 47 FP shops and from November onwards, FP shops are increased to 100. The total ration cards in the FP shop is around 66000. On an average, each FP shop consists of 600 below poverty line (BPL) families. The figure 7.2 shows the authentication attempts against Aadhaar along with success and failure attempts. The figure 7.3 gives the authentication percentages with fingerprints and without fingerprints (supervisor, and OTP).

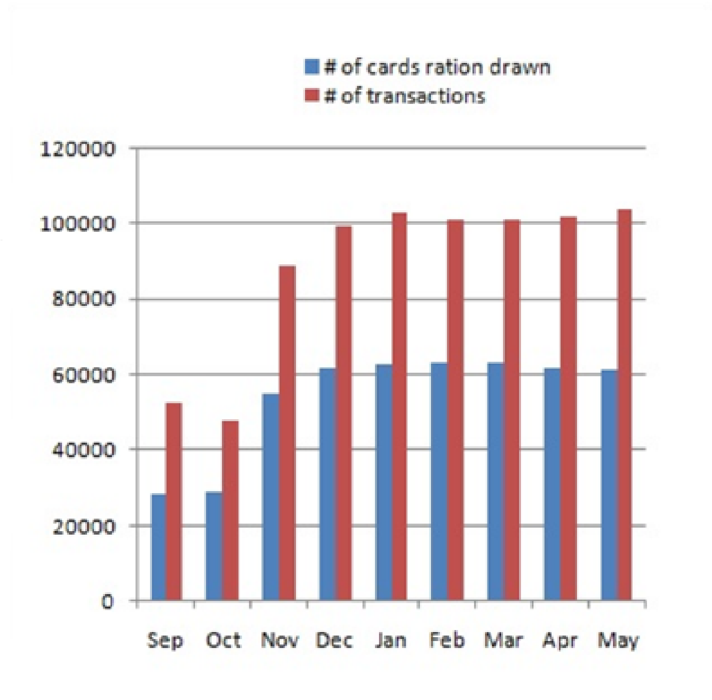


Fig. 7.1: Transaction trend of the proposed system

It is observed that the failure-to-capture rate exists for the people who work with heavy equipment, old aged, people diagnosed with leprosy, have very dry fingers, have very wet fingers and have shivering hands. Nearly 60% of the people are able to authenticate within the first attempt and 30% to 35 % people are able to authenticate within 2-3 attempts. It is observed that the very less percentage of people with 0.5% are not able to authenticate, mainly due to old age or leprosy. Each fair price shop consists on an average of 600 cards, nearly 2 to 3 people are not able to authenticate with their fingers. These people were authenticated through mandal revenue officer (MRO) to do transaction without fingerprint authentication.

The fingerprint based Aadhaar authentication has been implemented in the 100

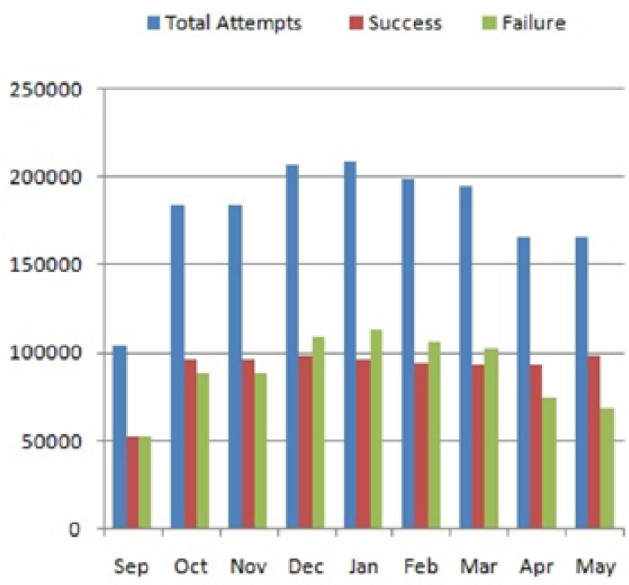


Fig. 7.2: Authentication attempts monthly, with Aadhaar database

fair price shops in Andra Pradesh, India. It is observed that the process is faster than the traditional method of smart-card based authentication. In e-governance, this is the first application which issues subsidy through online authentication in India. The program showed the loopholes in the PDS system how much leakage is happening. It is observed that nearly 25% savings in urban areas, 15% to 20% in rural areas, and nearly 30% savings in tribal areas. The advantages of this system are that people will know the stock arrival through SMS and nobody can take one person benefits on behalf of others. It provides lot of transparency in the system through on line public portal.

7.4.2 Student time and attendance system and its proof of concept

As part of the student's time and attendance system proof of concept, five courses (C1, C2, C3, C4 and C5) are considered for 160 students. The faculty members allotted for courses C1 and C4 are one, for course C2 are two, for course C3 are three and for course C5 are 10. The proof of concept is conducted for one semester and

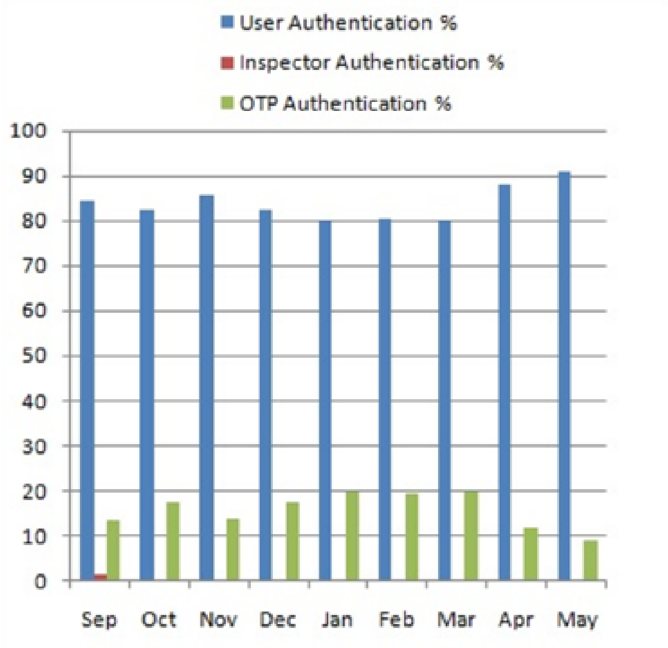


Fig. 7.3: Monthly authentication percentage, with fingerprints, supervisor, and OTP

the attendance percentage for every student is plotted as shown in the figure 7.4. It is observed that the fingerprint authentication is accurate over the semesters. The attendance percentage when compared over the manual attendance both approaches validated and given the same results, with this approach manual work has reduced. As part of proof of concept both manual and automatic attendance have been taken parallel to compare the accuracy.

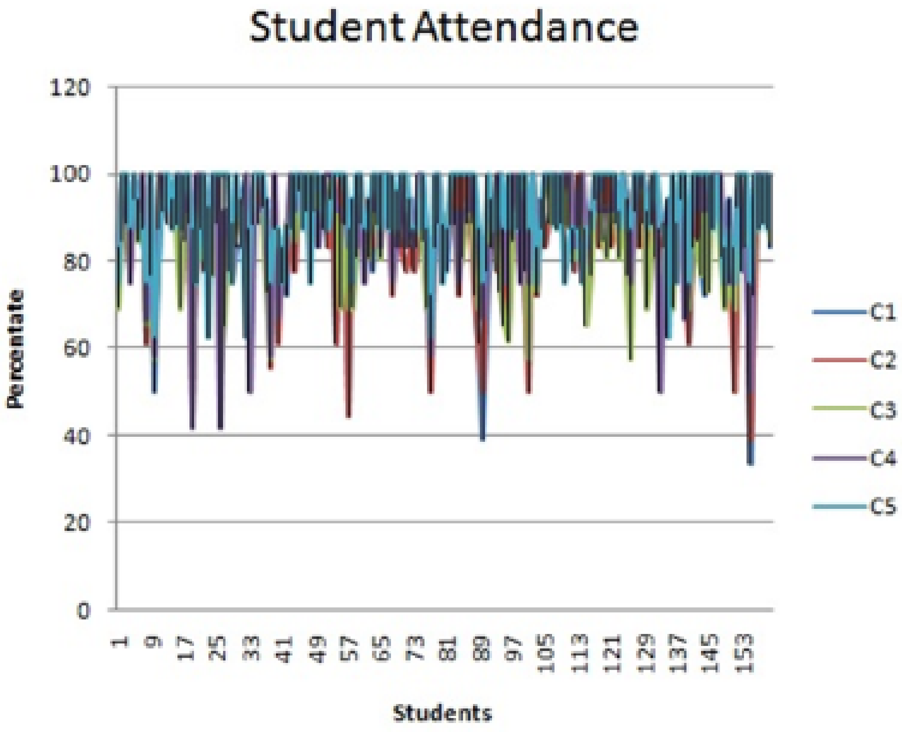


Fig. 7.4: Student attendance for five courses

7.5 SUMMARY

In this chapter, we make use of the approaches proposed in the previous chapters for two different fingerprint based authentication systems in the fields of e-governance and academia. The first study utilized Aadhaar authentication in fair price (FP) shops(ration shops) of Andhra Pradesh, India for distributing ration. The study suggests that the proposed approach is able to bring the transparency in the system and benefits to customers and Government. It is also observed that this process is faster than the traditional method of distributing commodities with smart-card based authentication. A proof of concept (POC) is conducted on taking student attendance through hand-held biometric devices by eliminating the traditional paper based attendance. Based on the observations made in real-time, the proposed approach is more reliable.

CHAPTER 8

CONCLUSIONS AND FUTURE WORK

In this thesis, we have proposed efficient methods for plain and latent fingerprint, and palmprint recognition, to reduce space and time of matching algorithms. A cross comparison of fingerprint optical authentication sensors have been illustrated by capturing the fingerprint samples with three different optical sensors. We have compared the performance of these authentication sensors with different matching techniques and illustrated the results. The nearest neighbor and quadruplet based minutiae matching algorithm for plain fingerprint verification is proposed. The proposed fingerprint algorithm achieved better results on standard FVC databases. A semi-automated latent fingerprint recognition that avoids human intervention in recognising latent fingerprints is proposed. The proposed semi-automated latent fingerprint recognition is evaluated on standard latent database FVC SD 27. A high resolution palmprint based recognition that uses minutiae quadruplets which is independent of segmenting of palmprint is proposed. Experimental study suggests that the proposed algorithm improves the performance of the high resolution palmprint matching. A real time Aadhaar based public distribution system to demonstrate the benefits of biometrics in large-scale applications is developed. The proposed real time large scale fingerprint application in public distribution system is able to eradicate the fraud involved with the existing manual system. The problems involved in the process of implementing large scale applications are demonstrated, and also the best practises to be followed in large scale applications.

8.1 CONTRIBUTIONS OF THE WORK

The contributions of this research work are summarized below:

1. Fingerprint authentication based sensors performance is evaluated with different matching algorithms. A global minutiae matching algorithm is proposed and the performance of the algorithm is evaluated with open source NIST Bozorth algorithm. The fingerprints from users using three different authentication sensors with optical technology are collected. The algorithms are evaluated on the database of fingers collected with these different sensors. The proposed algorithm shows very good accuracy in all the combinations over the Bozorth algorithm.
2. An improved hybrid fingerprint recognition technique for plain fingerprints using minutiae quadruplets is proposed to reduce the space and time complexity. The proposed nearest neighbor minutiae quadruplet matching technique with reduced time and space complexity achieves comparable performance when evaluated on public data bases from FVC ongoing and FVC 2000, 2004.
3. A new semi-automated latent fingerprint matcher using global minutiae is proposed to improve the performance of fingerprint matching. The proposed method achieves better accuracy on publicly available database NIST SD27 special database when compared to NIST Bozorth algorithm.
4. A palmprint based recognition technique on entire palmprint with out segmenting using minutiae quadruplets is presented to improve the accuracy of palmprint recognition. The high resolution palmprint matching techniques are based on segmenting the palm into segments and then doing matching, in order to reduce the time and space complexities. This high resolution palmprint algorithm based on the full palmprint matching technique does not use segmenting. The performance of algorithm is evaluated on the public data sets from FVC and THUPALAM LAB.

5. A real time mobile fingerprint authentication is presented using the India's Aadhaar infrastructure and mobile device with fingerprint sensor. The proposed e-Governance application is designed to streamline the distribution of commodities. The system proved beneficial to government and to end-users, by eradicating frauds involved with the manual process.
6. The best practices for biometric data acquisition and identity creation is presented. Best practises in handling the large scale applications is also presented.

8.2 DIRECTIONS FOR FUTURE RESEARCH

In this thesis, we have proposed an efficient approaches for fingerprint and palmprint recognition in large scale applications. The main objective of these approaches are to reduce the space and time complexities with out compromising the accuracy. A nearest neighbor minutiae matching technique with combination of minutiae quadruplets is proposed to reduce the space and time complexities. Most of the minutiae based matching techniques are based on fixed radius based structures or based on graph based similarity. These matching techniques accuracy is much prone to missing minutiae. There is need for exploring the matching techniques in case of fingerprint images with very less common area. Even the matching efficiency with quintuplets can be explored. Similarly, for the palmprint matching there is a need for improvement in the matching time. As the palmprint is sixteen to twenty time larger in size, the matching time for a single palm print is 100 times slow when compared with fingerprint matching. By decreasing the number of neighbors in the nearest neighbor matching stage, the matching time can be further reduced. Still there is scope for further improvement in the space and time complexities of palmprint recognition.

In this thesis a comparative study of different optical fingerprint sensors using different matching techniques is performed. The results suggests that the performance of matching is not dependent on the size of the image captured from the sensors. There is a chance to explore the image capturing from sensors, to capture the bulb area of the fingerprint always. If the captured area is common from capture to capture, the accuracy of the recognition performance will be improved. The proposed automated latent fingerprint recognition is not yet achieved very good results with latent fingerprint of very poor quality. The efficient feature extraction techniques need to be explored for the poor latent fingerprints to improve the accuracy of latent fingerprint recognition.

REFERENCES

[1] H. C. Lee and R. E. G. (editors), "Advances in fingerprint technology," in *Elsevier*, New York, 1991.

[2] S. P. A. K. Jain, L. Hong and R. Bolle, "An identity authentication system using fingerprints," *Proceedings of the IEEE*, vol. 85, no. 9, pp. 1365–1388, 1997.

[3] A. R. Pai, "Palmprint quality - parameters & enhancement," in *http://www.cse.iitk.ac.in/users/atulrpai/palmprint.html*.

[4] W. Jia, Y. H. Zhu, L. F. Liu, and D. S. Huang, "Fast palmprint retrieval using principal lines," in *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on*, pp. 4118–4123, Oct 2009.

[5] A. Negi, B. Panigrahi, M. V. N. K. Prasad, and M. Das, "A palmprint classification scheme using heart line feature extraction," in *Information Technology, 2006. ICIT '06. 9th International Conference on*, pp. 180–181, Dec 2006.

[6] UIDAI, "The unique identification authority of india," *http://uidai.gov.in/*.

[7] D. Maio and D. Maltoni, "Direct gray-scale minutiae detection in fingerprints," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 1, pp. 27–40, Jan 1997.

[8] "Early history of fingerprints," *http://onin.com/fp/fphistory.html*.

[9] D. Maltoni, "A tutorial on fingerprint recognition," in *http://www.cedar.buffalo.edu/ govind/CSE666/fall2007/FP$_T$utorial.pdf*.

[10] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, *Handbook of fingerprint recognition.* springer, 2009.

[11] W. A. Kass, M., "Analyzing oriented patterns," *Computer Vision, Graphics, and Image Processing*, vol. 37, no. 3, no. 3, pp. 0362–0385, 1987.

[12] C. S. Ratha, N.K. and A. Jain, "Adaptive flow orientation-based feature extraction in fingerprint images," *Pattern Recognition*, vol. 28, no. 11, pp. 1657–1672, 1995.

[13] A. M. Bazen and S. H. Gerez, "Systematic methods for the computation of the directional fields and singular points of fingerprints," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 905–919, Jul 2002.

[14] W. R. Gonzales, R.C., *Digital Image Processing.* Addison-Wesley, Reading, MA, 1992.

[15] H. Fleyeh, E. Davami, and D. Jomaa, "Segmentation of fingerprint images based on bilevel processing using fuzzy rules," in *Fuzzy Information Processing Society (NAFIPS), 2012 Annual Meeting of the North American*, pp. 1–6, Aug 2012.

[16] L. Hong, Y. Wan, and A. Jain, "Fingerprint image enhancement: algorithm and performance evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777–789, Aug 1998.

[17] L. Lam, S. W. Lee, and C. Y. Suen, "Thinning methodologies-a comprehensive survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 9, pp. 869–885, Sep 1992.

[18] D. K. Karna, S. Agarwal, and S. Nikam, "Normalized cross-correlation based fingerprint matching," in *Fifth International Conference on Computer Graphics, Imaging and Visualisation, 2008. CGIV '08.*, pp. 229–232, Aug 2008.

[19] A. Lindoso, L. Entrena, J. Liu-Jimenez, and E. S. Millan, "Increasing security with correlation-based fingerprint matching," in *2007 41st Annual IEEE International Carnahan Conference on Security Technology*, pp. 37–43, Oct 2007.

[20] A. Lindoso, L. Entrena, C. Lopez-Ongil, and J. Liu, "Correlation-based fingerprint matching using fpgas," in *Proceedings. 2005 IEEE International Conference on Field-Programmable Technology, 2005.*, pp. 87–94, Dec 2005.

[21] J. F. Lim and R. K. Y. Chin, "Enhancing fingerprint recognition using minutiae-based and image-based matching techniques," in *1st International Conference on Artificial Intelligence, Modelling and Simulation (AIMS),*, pp. 261–266, Dec 2013.

[22] V. Cantoni, L. Lombardi, and P. Lombardi, "Most minutiae-based matching algorithms confront," in *18th International Conference on Pattern Recognition (ICPR'06)*, vol. 4, pp. 378–385, Aug 2006.

[23] H. Choi, K. Choi, and J. Kim, "Fingerprint matching incorporating ridge features with minutiae," *IEEE Transactions on Information Forensics and Security*, vol. 6, no. 2, pp. 338–345, June 2011.

[24] H. Wei, Z. Ou, and J. Zhang, "Fingerprint identification based on ridge lines and graph matching," in *2006 6th World Congress on Intelligent Control and Automation*, vol. 2, no. 1, pp. 9965–9968, 2006.

[25] A. N. Marana and A. K. Jain, "Ridge-based fingerprint matching using hough transform," in *XVIII Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI'05)*, pp. 112–119, Oct 2005.

[26] A. M. Bazen and S. H. Gerez, "Fingerprint matching by thin-plate spline modelling of elastic deformations," *Pattern Recognition*, vol. 36, no. 8, pp. 1859–1867, 2003.

[27] A. Wahab, S. Chin, and E. Tan, "Novel approach to automated fingerprint recognition," *Vision, Image and Signal Processing*, vol. 145, no. 3, pp. 160–166, 1998.

[28] D. R. Ashbaugh and C. Press, *Quantitative-qualitative friction ridge analysis: an introduction to basic and advanced ridgeology.* CRC press Boca Raton, 1999.

[29] J. Qi and Y. Wang, "A robust fingerprint matching method," *Pattern Recognition*, vol. 38, no. 10, pp. 1665–1671, 2005.

[30] N. K. Ratha, K. Karu, S. Chen, and A. K. Jain, "A real-time matching system for large fingerprint databases," *, IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 8, pp. 799–813, 1996.

[31] A. Ross, A. Jain, and J. Reisman, "A hybrid fingerprint matcher," *Pattern Recognition*, vol. 36, no. 7, pp. 1661–1673, 2003.

[32] X. Luo, J. Tian, and Y. Wu, "A minutiae matching algorithm in fingerprint verification," in *Pattern Recognition, 15th IEEE International Conference on*, vol. 4, pp. 833–836, 2000.

[33] N. K. Ratha, R. M. Bolle, V. D. Pandit, and V. Vaish, "Robust fingerprint authentication using local structural similarity," pp. 29–34, 2000.

[34] X. Chen, J. Tian, and X. Yang, "A new algorithm for distorted fingerprints matching based on normalized fuzzy similarity measure," *IEEE Transactions on Image Processing*, vol. 15, no. 3, pp. 767–776, 2006.

[35] F. M. D. F. Sheng W, Howells G, "A memetic fingerprint matching algorithm," *IEEE Trnasactions on Information Forensics and Security*, vol. 2, no. 3, pp. 402–412, 2007.

[36] P. S. Jain A., Ross A., "Fingerprint matching using minutiae and texture features," in *Conference on Image Processing (ICIP)*, pp. 282–285, 2001.

[37] R. Z. Q. S. Jie Y., Yi fang Y., "Fingerprint minutiae matching algorithm for real time system," *Pattern Recognition*, vol. 39, no. 1, pp. 143–146, 2006.

[38] C. S. Germain R.S., Califano A., "Fingerprint matching using transformation parametre clustering," *IEEE Computational Science and Engineering.*, vol. 4, no. 4, pp. 42–49, 1997.

[39] H. Choi, M. Boaventura, I. A. G. Boaventura, and A. K. Jain, "Automatic segmentation of latent fingerprints," in *IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS),*, pp. 303–310, Sept 2012.

[40] J. Feng, "Combining minutiae descriptors for fingerprint matching," *Pattern Recognition*, vol. 41, no. 1, pp. 0342–0352, 2008.

[41] A. K. Jain and J. Feng, "Latent fingerprint matching," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 1, pp. 88–100, 2011.

[42] A. Kong, D. Zhang, and M. Kamel, "A survey of palmprint recognition," *Pattern Recognition*, vol. 42, no. 7, pp. 1408 – 1418, 2009.

[43] A. J. N. Duta and K. Mardia, "Matching of palmprints," *Pattern Recognition Letters*, vol. 23, no. 4, pp. 0477–0485, 2002.

[44] W. Shu and D. Zhang, "Automated personal identification by palmprint," *Optical Engineering*, vol. 38, no. 8, pp. 2359–2362, 1998.

[45] "Early history of palmprints," *http://www.jade1.com/jadecc/courses/UNIVERSAL/NEC05.php?imDif=6472.0.*

[46] M. L. F. Li and X. Yu, "Palmprint identification using hausdorff distance," in *International Workshop on Biomedical Circuits and Systems*, pp. 003–008, 2004.

[47] K. W. X. Wu and D. Zhang, "Line feature extraction and matching in palmprint," in *Second International Conference on Image and Graphics*, pp. 0583–0590, 2002.

[48] J. A. M. Rafael Diaz, C.M. Travieso and M. Ferrer, "Biometric system based in the feature of hand palm," in *38th Annual International Carnahan Conference on Security Technology*, pp. 0136–0139, 2004.

[49] K. W. X. Wu and D. Zhang, "A novel approach of palm-line extraction," in *Third International Conference on Image and Graphics*, pp. 0230–0233, 2004.

[50] P. R. Rodrigues and J. L. Silva, "Biometric identification by dermatoglyphics," *International Conference on Image Processing*, vol. 1, no. 1, pp. 0319–0322, 1996.

[51] J. Canny, "A computational approach to edge detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 8, no. 6, pp. 0450–0463, 1986.

[52] K. W. X. Wu and D. Zhang, "Fuzzy direction element energy feature (fdeef) based palmprint identification," in *International Conference on Pattern Recognition*, pp. 0095–0098, 2002.

[53] W. Boles and S. Chu, "Personal identification using images of the human palms," in *Speech and Image Technologies for Computing and Telecommunications*, pp. 0295–0298, 1997.

[54] M. O. T. Connie, A.T.B. Jin and D. Ling, "An automated palmprint recognition system," *Image and Vision Computing*, vol. 23, no. 5, pp. 0501–0515, 2005.

[55] D. Z. X. Wu and K. Wang, "Fisherpalms based palmprint recognition," *Pattern Recognition Letters*, vol. 24, no. 15, pp. 2829–2838, 2003.

[56] D. Z. G. Lu and K. Wang, "Fisherpalms based palmprint recognition," *Pattern Recognition Letters*, vol. 24, no. 9, pp. 1463–1467, 2003.

[57] D. H. G. Feng, K. Dong and D. Zhang, "When face are combined with palmprints: a novel biometric fusion strategy," *Lecture Notes in Computer Science, Springer*, vol. 3072, no. 1, pp. 0701–0707, 2004.

[58] D. Z. G. Feng, D. Hu and Z. Zhou, "An alternative formulation of kernel lpp with application to image recognition," *Neurocomputing*, vol. 67, no. 15, pp. 1733–1738, 2006.

[59] J. G. H. Z. W. Deng, J. Hu and C. Zhang, "Comment on globally maximizing locally minimizing: unsupervised discriminant projection with applications to face and palm biometrics," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 8, pp. 1503–1504, 2008.

[60] J. Y. J. Yang, D. Zhang and B. Niu, "Globally maximizing locally minimizing:unsupervised discriminant projection with applications to face and palm biometrics," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 0650–0664, 2007.

[61] K. W. Y. Li and D. Zhang, "Palmprint recognition based on translation invariant zernike moments and modular neural network," *Lecture Notes in Computer Science, Springer*, vol. 3497, no. 1, pp. 0177–0182, 2005.

[62] J. Noh and K. Rhee, "Palmprint identification algorithm using hu invariant moments and otsu binarization," in *Fourth Annual ACIS International Conference on Computer and Information Science*, pp. 0094–0099, 2005.

[63] D. Z. K. C. J. You, W.K. Kong, "On hierarchical palmprint coding with multiple features for personal identification in large databases," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, no. 2, pp. 0234–0243, 2004.

[64] A. Kumar and D. Zhang, "Palmprint authentication using multiple classifiers," in *SPIE Symposium on Defence and Security- Biometric Technology for Human Identification*, pp. 0020–0029, 2004.

[65] D. W. C. Poon and H. Shen, "Personal identification and verification: fusion of palmprint representations," in *International Conference on Biometric Authentication*, pp. 0782–0788, 2004.

[66] H. Z. B. L. X. Wang, H. Gong and Z. Zhuang, "Palmprint identification using boosting local binary pattern," in *International Conference on Pattern Recognition*, pp. 0503–0506, 2006.

[67] R. Guerrieri, "Capacitive sensing technology," in *http://www-micro.deis.unibo.it/t̃artagni/Finger/FingerSensor.html.*

[68] Biometrika, "Optical sensing technology," in *http://www.biometrika.it/eng/wp_fingintro.html.*

[69] M. U. Akram, S. Nasir, A. Tariq, I. Zafar, and W. S. Khan, "Improved fingerprint image segmentation using new modified gradient based technique," in *IEEE Canadian Conference on Electrical and Computer Engineering*, pp. 1967–1972, 2008.

[70] J.-j. Gao and M. Xie, "The layered segmentation, gabor filtering and binarization based on orientation for fingerprint preprocessing," in *8th IEEE International Conference on Signal Processing*, pp. 1967–1972, 2008.

[71] X. Guo, G. Yang, and Y. Yin, "Sensor interoperability of fingerprint segmentation: An empirical study," in *IEEE International Conference on Information Engineering and Computer Science*, pp. 1–4, 2009.

[72] J. Qi and M. Xie, "Segmentation of fingerprint images using the gradient vector field," in *IEEE International Conference on Cybernetics and Intelligent Systems*, pp. 543–545, 2008.

[73] J.-Z. Cao and Q.-Y. Dai, "A novel online fingerprint segmentation method based on frame-difference," in *IEEE International Conference on Image Analysis and Signal Processing*, pp. 57–60, 2009.

[74] Z. Ma, M. Xie, and C. Yu, "Fingerprint segmentation based on pcnn and morphology," in *IEEE International Conference on Communications, Circuits and Systems*, pp. 566–568, 2009.

[75] A. K. J. S. P. D. Maltoni, D. Maio, "Handbook of fingerprint recognition," in *New York: Springer*, 2003.

[76] F. A. J. A. F. Fernando and O. G. Javier, "An enhanced gabor filter-based segmentation algorithm for fingerprint recognition systems," in *4th IEEE Int. Symposium on Image and Signal Processing and Analysis*, pp. 239–244, 2005.

[77] N. P. Ramaiah and C. K. Mohan, "De-noising slap fingerprint images for accurate slap fingerprint segmentation," in *10th IEEE Int. Conf. on Machine Learning and Applications*, pp. 208–211, 2011.

[78] M. G. M. Kaur and S. Sandhu, "Fingerprint verification system using minutia extraction technique," in *Proc. of World Academy of Science, Engineering and Technology*, pp. 497–502, Dec. 2008.

[79] M. Tarjoman and S. Zarei, "Automatic fingerprint classification using graph theory," in *Proc. of World Academy of Science, Engineering and Technology*, pp. 831–835, Jun. 2008.

[80] W. Liu, "Fingerprint classification using singularities detection," *Int. Journal of Mathematics and Computer in Simulation*, vol. 2, no. 2, pp. 158–162, 2008.

[81] A. Lumini and L. Nann, "Advanced methods for two-class pattern recognition problem formulation for minutiae-based fingerprint verification," *Pattern Recognition Letters*, vol. 29, no. 1, pp. 286–294, Jan. 2008.

[82] J.-H. H. X.-F. Tong, S.-B. Liu and X.-L. Tang, "Local relative location error descriptor-based fingerprint minutia matching," *Pattern Recognition Letters*, vol. 29, no. 3, pp. 286–294, Feb. 2008.

[83] A. K. Jain and J. J. Feng, "Latent fingerprint matching," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 33, no. 1, pp. 88–100, 2011.

[84] K. L. L. Li and N. He, "An improved cross-matching algorithm for fingerprint images from multi-type sensors," in *Proc. of the 4th Int. Conf. on Image and Signal Processing*, pp. 1472–1475, 2011.

[85] S. B. M. Vatsa, R. Singh and H. Bhat, "Analyzing fingerprints of indian population using image quality: A uidai case study," in *Proc. of Emerging Techniques and Challenges of Hand-Based Biometrics*, pp. 1–5, 2011.

[86] J. A. P. S. Maltoni D, Mario D, *Handbook fo Fingerprint Recognition*. Springer, 2003.

[87] Z. H. Liu N, Yin Y, "Fingerprint matching algorithm based on delauny triangulation net," in *Proceedings of the fifth International Conference on Computer and information Technology*, pp. 591 – 595, 2005.

[88] D. M. Jain A, Chen Y, "Pores and ridges: Fingerprint matching using level 3 features," in *The 18th International Conference on Pattern Recognition (ICPR'06)*, pp. 477 – 480, 2006.

[89] M.Tico and P.Kuosmanen, "Fingerprint matching using an orientation-based minutia descriptor," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 25, no. 8, pp. 1009–1014, 2003.

[90] A. M.Medina-perez and M.G.Borroto, "Improving fingerprint matching using an orientationbased minutia descriptor," in *Conference on Pattern Recognition (CIARP)*, pp. 0001–0004, 2009.

[91] X. G.S.Ng, X.Tong and D.Shi, "Adjacent orientation vector based fingerprint minutiae matching system," in *Interanational Conference on Pattern Recognition*, pp. 0528–0531, 2004.

[92] J.Qi and Y.Wang, "A robust fingerprint matching method," *Pattern Recognition*, vol. 38, no. 1, pp. 1665–1671, 2005.

[93] Z. J.Feng and A.Cai, "Fingerprint matching using ridges," *Pattern Recognition*, vol. 39, no. 1, pp. 2131–2140, 2006.

[94] L. Y. Y.He, J.Tian and X.Yang, "Fingerprint matching based on global comprehensive similarity," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 28, no. 6, pp. 0850–0862, 2006.

[95] J. E.Zhu and G.Zhang, "Fingerprint matching based on global alignment of multiple reference minutiae," *Pattern Recognition*, vol. 38, no. 1, pp. 1685–1694, 2005.

[96] X. W.Xu and J.Feng, "A robust fingerprint matching approach:growing and fusing of local structures," *Lecture Notes in Computer Science*, pp. 4642–4643, 2007.

[97] J. X.Chen, J.Tian and Y.Zhang, "An algorithm for distorted fingerprint matching based on local triangle feature set," *IEEE Trans. Information Forensics and Security*, vol. 1, no. 2, pp. 0169–0179, 2006.

[98] X.Jiang and W.Y.Yau, "Fingerprint minutiae matching based on the local and global structures," *Pattern Recognition*, vol. 2, no. 1, pp. 6038–6041, 2000.

[99] R. N.K.Ratha, V.D.Pandit and V.Vaish, "Robust fingerprint authentication using local structural similarity," in *IEEE Workshop Applications of Computer Vision*, pp. 0029–0034, 2000.

[100] M. R.Cappelli and D.Maltoni, "Minutia cylinder-code: A new representation and matching technique for fingerprint recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 32, no. 12, pp. 2128–2141, 2010.

[101] T. A.Jeuls, P.Tuyls and B.Skoric, "Fuzzy commitment. security with noisy data-on private biometrics," in *Secure Key Storage and Anti-Counterfeiting*, pp. 0045–0056, 2007.

[102] T. A. R. P.Tuyls, A.Akkermans and G.Schrijen, "Practical biometric authentication with template protection," in *Audio- and video-based biometric person authentication (AVBPA)*, pp. 0436–0446, 2005.

[103] M. F. D. M. D. M. N. H. S. G.-S. B. Dorizzi, R. Cappelli and A. Mayoue, "Fingerprint and on-line signature verification competitions at icb 2009," in *Proceedings International Conference on Biometrics (ICB), Alghero, Italy*, pp. 725–732, 2009.

[104] F. Ongoing, "k-nearest neighbor and quadruplet based minutiae matching algorithm on iso matching," in *https://biolab.csr.unibo.it/FvcOnGoing/UI/Form/AlgResult.aspx?algId=4548.*

[105] F. Ongoing, "k-nearest neighbor and quadruplet based minutiae matching algorithm on finger verification," in *https://biolab.csr.unibo.it/FvcOnGoing/UI/Form/AlgResult.aspx?algId=4611.*

[106] NIST, "Nist special database 27," in *http://www.nist.gov/srd/nistsd27.cfm.*

[107] P. Shi, J. Tian, Q. Su, and X. Yang, "A novel fingerprint matching algorithm based on minutiae and global statistical features," in *Proceedings Biometrics: Theory, Applications, and Systems,*, pp. 1–6, Sept 2007.

[108] S. Yoon, J. Feng, and A. K. Jain, "Altered fingerprints: Analysis and detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 3, pp. 451–464, March 2012.

[109] X. Chen, J. Tian, X. Yang, and Y. Zhang, "An algorithm for distorted fingerprint matching based on local triangle feature set," *IEEE Transactions on Information Forensics and Security*, vol. 1, no. 2, pp. 169–177, June 2006.

[110] J. T. Xinjian Chen and X. Yang, "A new algorithm for distorted fingerprints matching based on normalized fuzzy similarity measure," *IEEE Transactions on Image Processing*, vol. 15, no. 3, pp. 767–776, 2006.

[111] J. T. Xiping Luo and Y. Wu, "A minutiae matching algorithm in fingerprint verification," *15th IEEE International Conference on Pattern Recognition*, vol. 4, pp. 833–836, 2010.

[112] V. D. P. Nalini K Ratha, Ruud M Bolle and V. Vaish, "Robust fingerprint authentication using local structural similarity," in *IEEE Workshop on Applications of Computer Vision*, pp. 29–34, 2010.

[113] J. Qi and Y. Wang, "A robust fingerprint matching method," *Pattern Recognition*, vol. 38, no. 10, pp. 1665–1671, 2005.

[114] S. C. Nalini K Ratha, Kalle Karu and A. K. Jain, "A real-time matching system for large fingerprint databases," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 8, pp. 799–813, 1996.

[115] A. J. Arun Ross and J. Reisman, "A hybrid fingerprint matcher," *Pattern Recognition*, vol. 36, no. 7, pp. 1661–1673, 2013.

[116] T.-Y. Jea and V. Govindaraju, "A minutia-based partial fingerprint recognition system," *Pattern Recognition*, vol. 38, no. 10, p. 16721684, 2005.

[117] R. C. J. L. W. Dario Maio, Davide Maltoni and A. K. Jain, "Fvc2002: Second fingerprint verification competition," *16th International Conference on Pattern Recognition*, vol. 3,no. 1, pp. 0811–0814, 2002.

[118] L. OGorman and J. V. Nickerson, "An approach to fingerprint filter design," *Pattern Recognition*, vol. 22, no. 1, pp. 29–38, 1989.

[119] Z. Guo and R. W. Hall, "Parallel thinning with two-subiteration algorithms," *Communications of the ACM*, vol. 32, no. 3, pp. 359–373, 1989.

[120] S. P. Anil K Jain and L. Hong, "A multichannel approach to fingerprint classification," *IEEE Transactions on PatternAnalysis and Machine Intelligence*, vol. 21, no. 4, pp. 348–359, 1999.

[121] Q. Xiao and H. Raafat, "Fingerprint image postprocessing: a combined statistical and structural approach," *Pattern Recognition*, vol. 24, no. 10, pp. 985–992, 1991.

[122] a. S. ZhaoQi Bian, David Zhang, "Knowledge based fingerprint post-processing," *International journal of pattern recognition and artificial intelligence*, vol. 16, no. 1, pp. 53–67, 2012.

[123] A. K. Hrechak and J. A. McHugh, "Automated fingerprint recognition using structural matching," *Pattern Recognition*, vol. 23, no. 8, pp. 893–904, 1990.

[124] "Iso/iec 19794-2:2005," *Information TechnologyBiometric Data Interchange FormatsPart 2: Finger Minutiae Data*, 2005.

[125] M. D. Garris and R. M. McCabe, "Nist special database 27: Fingerprint minutiae from latent and matching tenprint images," *Disponıvel em¡ http://www. itl. nist. gov/iaui/894.03/databases¿. Acesso em: June*, 2000.

[126] "Fbi," *https://www.fbi.gov/about-us/cjis/fingerprints$_b$iometrics/biometric − center − of − excellence/files/palm − print − recognition.pdf.*

[127] I. Awate and B. Dixit, "Palm print based person identification," in *Computing Communication Control and Automation (ICCUBEA), 2015 International Conference on*, pp. 781–785, Feb 2015.

[128] K. Ito, T. Sato, S. Aoyama, S. Sakai, S. Yusa, and T. Aoki, "Palm region extraction for contactless palmprint recognition," in *Biometrics (ICB), 2015 International Conference on*, pp. 334–340, May 2015.

[129] A. George, G. Karthick, and R. Harikumar, "An efficient system for palm print recognition using ridges," in *Intelligent Computing Applications (ICICA), 2014 International Conference on*, pp. 249–253, March 2014.

[130] J. Y. D. Zhang, W.K. Kong and M. Wong, "Online palmprint identification,," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, no. 9, pp. 1041–1050, 2003.

[131] D. Z. W. Li and Z. Xu, "Palmprint identification by fourier transform," *Pattern Recognition and Artificial Intelligence*, vol. 16, no. 4, pp. 417–432, 2002.

[132] W. L. J. You and D. Zhang, "Hierarchical palmprint identification via multiple feature extraction," *Pattern Recognition*, vol. 35, no. 4, pp. 847–859, 2002.

[133] A. J. N. Duta and K. Mardia, "Matching of palmprints," *Pattern Recognition Letters*, vol. 23, no. 4, pp. 477–486, 2002.

[134] A. Jain and J. Feng, "Latent palmprint matching," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 31, no. 6, pp. 1032–1047, June 2009.

[135] J. Dai and J. Zhou, "Multifeature-based high-resolution palmprint recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 33, no. 5, pp. 945–957, May 2011.

[136] K. Saeed, M. Tabedzki, M. Rybnik, and M. Adamski, "K3m: A universal algorithm for image skeletonization and a review of thinning techniques," *International Journal of Applied Mathematics and Computer Science*, vol. 20, no. 2, pp. 317–335, 2010.

[137] "Thupalmlab palmprint database," *http://ivg.au.tsinghua.edu.cn/index.php ?n=Data.Tsinghua500ppi*.

[138] J. Dai and J. Zhou, "Multifeature-based high-resolution palmprint recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 33, no. 5, pp. 945–957, 2011.

[139] J. Dai, J. Feng, and J. Zhou, "Robust and efficient ridge-based palmprint matching," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 34, no. 8, pp. 1618–1632, 2012.

[140] "The unique identification authority of india," in *http://uidai.gov.in/*.

[141] "Gemalto, ehealthcare solutions-sergio popular," in *http://www.gemalto.com/brochures/download/mexico.pdf*, 2004.

[142] "Suprema solutions," in *https://www.supremainc.com/en/AccessControl-TimeandAttendance/Biometric-Devices/BioLite-Net*.

[143] "First aadhaar based pds," *http://www.thehindu.com/todays-paper/tp-national/aadhaarlinked-pds-east-godavari-shows-the-way/article3864157.ece*, Nov 2012.

[144] "e-governance awards," *http://www.thehindu.com/todays-paper/tp-national/tp-andhrapradesh/watching-aadhaar-card-anniversary-from-fp-shop/article4018688.ece*, Nov 2012.

List of Publications

CONFERENCES

1. A. Tirupathi Rao, N. Pattabhi Ramaiah and C. Krishna Mohan, "Palmprint Recognition based on Minutiae Quadruplets," in *Proc. Springer International Conference on Computer Vision and Image Processing(CVIP 2016)*, IIT Roorkee, Feb, 2016.

2. A Tirupathi Rao, N. Pattabhi Ramaiah, V. Raghavendra Reddy and C. Krishna Mohan, "Nearest Neighbor Minutia Quadruplets based Fingerprint Matching with Reduced Time and Space Complexity," in *Proc. 14Th IEEE International Conference on Machine Learning and Applications(ICMLA 2015)*, Miami, Florida, pp. 378-381, Dec. 2015.

3. A. Tirupathi Rao, and C. Krishna Mohan, "Best Practices for Biometric-based Identity creation in the E-Society," in *Proc. Elsevier S&T Int. Conf. on Advances in Information Technology and Mobile Communication (ICAIM 2015)*, Bangalore, India, PP. 75-80, Aug. 2015.

4. A Tirupathi Rao, N. Pattabhi Ramaiah and C. Krishna Mohan, "Enhancements to latent fingerprints in forensic applications," in *Proc. 19Th IEEE International Conference on Digital Signal Processing(DSP 2014)*, Hong Kong, pp. 439-443, Aug. 2014.

5. A. Tirupathi Rao, N. Pattabhi Ramaiah and C. Krishna Mohan, "Biometrics in e-Governance & Academia using Hand-held Fingerprint terminals," in *Proc. Elsevier S&T Int. Conf. on Advances in Communication Network and Com-*

puting (ICCNC 2014), Chennai, India, pp. 653-658, Feb. 2014.

6. A. Tirupathi Rao, N. Pattabhi Ramaiah and C. Krishna Mohan, "Fingerprint Recognition on Various Authentication Sensors," in *Proc. International Conference on Signal, Image Processing and Applications (ICSIA 2013)*, Barcelona, Spain, pp. 139-143, Aug. 2013.

JOURNALS

1. A. Tirupathi Rao, N. Pattabhi Ramaiah and C. Krishna Mohan, "Efficient Fingerprint and Palmprint Matching based on Minutiae Quadruplets," Communicated to *IET Biometrics(IEEE)*, Jun. 2016.

2. A. Tirupathi Rao, N. Pattabhi Ramaiah and C. Krishna Mohan, "Latent Fingerprint Recognition using ISO 19794-2 Fingerprint Templates," *Journal of Recent Trends in Engineering and Technology*, vol.11, pp. 145-152, Jun. 2014.

CURRICULUM VITAE

1. **Name:** A. Tirupathi Rao

2. **Date of Birth:** 20^{th} May 1980

3. **Permanent Address:**

   S/o.A Pullarao

   G-8, SriRam Towers

   Kousalya Colony

   P.O. Bachupally - 500090

   Rangareddy Dist., Telangana, India

4. **Educational Qualifications:**

   - May 2016: Doctor of Philosophy in Computer Science and Engineering (Ph.D., Dept. of CSE, IIT Hyderabad, A.P., India)
   - May 2006: Master of Technology in Software Engineering (M.Tech., SJCE, Mysore, Karnataka., India)
   - May 2004: Bachelor of Technology in Computer Science and Engineering (B.Tech.,VRSEC, Vijayawada, A.P., India)

5. **Employment History:**

   - Dec 2006 - Nov 2008: Software Engineer in CMC Ltd., Hyderabad, A.P., India.
   - Dec 2008 - Oct 2011: Senior Software Engineer in 4G Identity Solutions Pvt. Ltd., Hyderabad, A.P., India.

- Oct 2011 - Dec 2012: Technical Lead in BioMoRF Systems Pvt. Ltd., Hyderabad, A.P., India.
- Jan 2013 - Feb 2015: Technical Lead in Lonesoft Technologies Pvt. Ltd., Hyderabad, A.P., India.
- Mar 2015 - Till Date: Product Lead in Technobrain India Pvt. Ltd., Hyderabad, A.P., India.

DOCTORAL COMMITTEE

1. **Chairperson:** Dr. M. V. Pandurangarao

2. **Guide:** Dr. C. Krishna Mohan

3. **Members:**

    - Dr. Bheemarjuna Reddy Tamma (Dept. of CSE)
    - Dr. K. Sri Rama Murthy (Dept. of EE)
    - Dr. J. Challa Subramanya Sastry (Dept. of Mathematics)