DESIGN OF MULTIPLE ENROLLMENT BASED FINGERPRINT RECOGNITION SYSTEMS

Fred Kaggwa

Reg NO: 2013/PhD/022

MSc. CS, University Of Twente, 2012

BCS. Mbarara University of Science and Technology, 2008

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Supervisors:

1. **Associate Professor John Ngubiri**
2. **Associate Professor Florence Tushabe**

DECLARATION

I hereby declare that this thesis is my original work and has never been submitted to any other institution of higher learning for any academic award to the best of my knowledge.

SIGNATURE …………………………..

DATE ………………………….

Fred Kaggwa

APPROVAL

This research has been under our supervision and has our approval for submission

SIGNATURE ……………………………..

DATE …………………………….

1st Supervisor

Associate Professor John Ngubiri

SIGNATURE ……………………………..

DATE …………………………….

2nd Supervisor

Associate Professor Florence Tushabe

DEDICATION

To my parents Mr. and Mrs. Harriet Kakande, brothers Kato Ivan, Kizza Steven, Kalule James and Sisters Babirye Agnes and Mariam Namugga who have greatly supported me during this whole period while undertaking this study. May the almighty God reward you and bless you.

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2. Kaggwa, F.; Ngubiri, J.; Tushabe, F. **Multiple enrollment based Fingerprint Recognition Systems: State of the Art Survey**. IJCIT Volume 04-Issue 02, March 2015 [Online]. Available: http://www.ijcit.com/archives/volume4/issue2/Paper040240.pdf

3. Kaggwa, Fred, John Ngubiri, and Florence Tushabe. "**Improving recognition performance in multiple enrollment based fingerprint recognition systems**." In Computer & Information Technology (GSCIT), 2015 Global Summit on, pp. 1-5. IEEE, 2015, ISBN: 978-1-4673-6586-4

4. Fred Kaggwa, John Ngubiri and Florence Tushabe. Article: **Gabor Filter-based Multiple Enrollment Fingerprint Recognition**. International Journal of Computer Applications 139(7):32-38, April 2016. Published by Foundation of Computer Science (FCS), NY, USA

5. Kaggwa, Fred; Ngubiri, John; Tushabe, Florence, "**Combined Feature Level and Score Level Fusion Gabor Filter-based Multiple Enrollment Fingerprint Recognition**", **Accepted in Conference** "IEEE SCOPES-2016 *International conference on Signal Processing, Communication, Power and Embedded System*"

STATEMENT OF CONTRIBUTIONS

A number of researchers have proposed the use of multiple enrollment to improve the efficiency of fingerprint recognition systems. However, multiple enrollment based fingerprint recognition systems (MEFRS) still suffer low recognition accuracies, poor matching speeds and high memory consumption. Also, most of the MEFRSs' have been designed mainly based on minutiae approaches excluding others such as correlation and pattern based approaches. These factors, make them difficult, expensive and limit their implementation in resource constrained applications. It was therefore important to provide interventions to design better multiple enrollment based fingerprint recognition systems that are implementable in real world applications.

This thesis improves recognition accuracy, reduces matching speed/running time as well as memory consumption in multiple enrollment based fingerprint recognition systems. It also experiments the use of a non-minutiae matching method (Gabor-filtering) to design multiple enrollment fingerprint recognition systems.

From a biometrics point of view, Multiple Enrollment and Fingerprint Recognition were the research topics of focus. The key targets of this work were; (i) to achieve a high recognition performance, (ii) to reduce matching speed, (iii) to reduce memory consumption and (iv) to use other fingerprint features while designing multiple enrollment based fingerprint recognition systems. Below, is a list of the main contributions of this thesis in association with the key targets and the thesis chapters (2-7). It is important to note that all the contributions are derived from the algorithms that were designed to achieve the research goals.

Chapter Two: Chapter two provides a literature survey that can serve as a quick overview of the state of the art in multiple enrollment for fingerprint recognition for the past two decades. This literature survey serves as a quick guide for reference by anyone who would want to carry out future research in the area of multiple enrollment for fingerprint recognition.

Chapter Three: This Chapter is the methodology and provides a new approach to designing multiple enrollment fingerprint recognition systems.

Chapter Four: The contribution of this chapter is a new multiple enrollment algorithm with improved recognition performance using a new fingerprint representation (minutiae spectrum). This was the first attempt of multiple enrollment experiments in this research and therefore other aspects such as computational/matching speed and memory consumption were not considered. A comparison with single enrollment and other multiple enrollment results in literature shows that our algorithms are superior in terms of recognition performance.

Chapter Five: This chapter provides a novel approach (algorithm) that performs prior selection of good fingerprint image samples of an individual for matching which further improves recognition performance, reduces the matching speed as well as memory consumption.

Chapter Six: The contribution of this chapter is a Gabor filter-based fingerprint recognition system design method; the first of the kind that implements a verification multiple enrollment based fingerprint recognition system. The recognition performance, matching speed as well as memory consumption results from this design method were not that good but however promising.

Chapter Seven: This chapter provides a Combined Feature Level and Score Level Fusion Gabor filter-based fingerprint recognition system design method; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system is presented. This system design method significantly improves the recognition performance, reduces the matching speed as well as memory consumption.

POLICY STATEMENT

This thesis deals with designing multiple enrollment fingerprint recognition systems that can be fit for deployment in real world applications/situations. As multiple enrollment fingerprint recognition comes to dominate single enrollment fingerprint recognition, it becomes more and more expensive to implement with in limited resources aka resource constrained environments. The untiring efforts of Biometrics Agencies, Software Development Companies, Researchers, Security Agencies and Governments can be perceived as novelties and experimentations that will drive them to realize the good practices and avoid a number of challenges whilst designing and developing multiple enrollment based fingerprint recognition systems. While it is true that some researchers often advocate the adoption of Multibiometrics (such as combining multiple fingerprint matchers, combining multiple fingerprint sensors and multiple modalities) that may improve recognition accuracy, their implementation, usability, high memory consumption, poor matching speeds and acceptability in real-world deployment situations/applications have still remained a challenge; it would require more costs to acquire the necessary extra computational resources, to implement as well as convincing and training users to adapt to them. The recognition accuracies are also still low. By strongly advocating for more stringent biometrics standards, governments should formulate robust multiple enrollment biometric systems development policies to persuade the novice multiple enrollment fingerprint recognition system designers and developers to look beyond their current personal design abilities and focus on broader real world application implementations. Such policies need to prioritize multiple enrollment using single modalities to allow for easy implementation, acceptability and usability, high recognition accuracies, reduced matching/comparison speeds and lower/reduced memory consumptions to achieve robust multiple enrollment fingerprint recognition systems that are deployable in real world applications/situations.

TERMINOLOGIES

The following are some of the different terminologies under multiple enrollment for fingerprint recognition and as used in the literature as well as other chapters that follow.

Table 1: Terminologies and their Descriptions

Terminology	Description
AAD	Average Absolute Deviation
AFIS	Automated Fingerprint Identification Systems
IAFIS	Integrated Automated Fingerprint Identification Systems
ATM	Automated Teller Machine
PIN	Personal Identification Number
FBI	Federal Bureau of Investigation
FVC	Fingerprint Verification Competition
EER	Equal Error Rate
FAR	False Acceptance Rate
FRR	False Rejection Rate
FpVTE	Fingerprint Vender Technology Evaluation
NIST	National Institute of Standards and Technology
DB1	Database One

DB2	Database Two
DB3	Database Three
Ms	Millisecond
ICT	Information Communication Technology
SAS	Signals and Systems
ID	Identification
2D	Two Dimension
MEFRS	Multiple Enrollment Fingerprint Recognition System

ABSTRACT

Using multiple enrollment can improve recognition performance in fingerprint recognition systems; but there are several technical and operational challenges to implementing multiple enrollment based fingerprint recognition systems. Multiple enrollment based fingerprint recognition systems still have low recognition accuracies, poor matching speeds, and consume a lot of memory making it difficult to implement them in real world scenarios. Also, most of multiple enrollment based fingerprint recognition systems have been designed mainly based on minutiae approaches but not others such as correlation and pattern based approaches hence limiting implementation. The purpose of this research was to provide a novel multiple enrollment fingerprint recognition approach that further improves recognition accuracy, the matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems as well as allow for implementation using non-minutiae methods. In this thesis, a literature survey of the state of the art in multiple enrollment for fingerprint recognition was first performed. A list of laboratories working on multiple enrollment for fingerprint recognition was also generated. This literature survey serves as a quick overview of the state of the art in multiple enrollment for fingerprint recognition for the past two decades. This thesis evaluates the effectiveness of using multiple enrollment in fingerprint recognition systems. A Spectral minutiae based multiple enrollment algorithm was designed and used together with existing fingerprint recognition techniques to carry out the evaluation. The experimentation results and evaluations show that multiple enrollment as whole outperforms single enrollment. Multiple enrollment in experiment one improved the recognition performance by 83.33% from EER of 0.75% to EER of 0.13% with FVC2000-DB2 fingerprint database, and by 75.55% from EER of 1.14% to EER of 0.28% with the SAS-DB2 fingerprint database. On the other hand, the multiple enrollment in experiment two improved the recognition performance by 71.51% from EER of 6.14% to EER of 1.75% with the FVC2000-DB2 fingerprint database and improved recognition performance by 53.61% from EER of 14.97% to EER of 6.94% with SAS-DB2 fingerprint database. A comparison with single enrollment and other multiple enrollment results in literature shows that our algorithms were superior by over 38.1% in terms of recognition performance. This research developed a novel approach that performs prior selection of good fingerprint image samples of an individual for matching and further improves recognition performance, reduces the matching speed as well as memory consumption. A spectral minutiae based matching method and two fingerprint databases (FVC2000-DB2 and FVC2006-DB2) were used. A comparison of our results with the existing ones presented in literature showed that they are more superior by over 29.6% with algorithm two (Alg2) and by 100% with algorithm three (*Alg3*). This makes it possible to design better multiple enrollment based fingerprint recognition systems with a high recognition accuracy, high matching speed and low memory consumption using our approach. This research also experimented with the Gabor filter-based approach; the first of the kind, to implement a verification multiple enrollment based fingerprint recognition system. The Gabor filter-based multiple enrollment fingerprint recognition method was compared with a spectral minutiae-based method using two fingerprint databases; FVC 2000-DB2-A and FVC 2006-DB2-A. Although the minutiae-based method outperformed the Gabor filter-based method, the results attained from the later were promising and were a good basis to further discussions and improvements for implementing Gabor filter-based techniques in designing multiple enrollment based fingerprint systems. This research embarked on a Combined Feature Level and Score Level Fusion Gabor filter-based approach; an advancement of the previous Gabor filter based method. The Combined Feature Level and Score Level Fusion Gabor filter-based multiple enrollment fingerprint recognition method was compared with a spectral minutiae-based method using the same (two) fingerprint databases as in the previous experimentation above. The results indicate that there is a significant percentage increase brought about by the combined feature level and Score Level fusion Gabor filter-based matching approach in comparison to the famous minutiae-based matching approach. The percentage increases in the FVC 2000-DB2-A fingerprint database were 86.45%, 98.01% and 87.82%, while those in the FVC 2006-DB2-A fingerprint database were 79.71%, 97.07% and 85.88% respectively for recognition performance improvement, matching speed improvement and memory consumption reduction. The results attained from the approach above were outstanding and are therefore a proposed possibility for future deployment in real world multiple enrollment fingerprint recognition applications that require better recognition performance, better matching speed and a reduced memory consumption.

Keywords: Fingerprint recognition, Multiple Enrollment, Gabor Filter-based Matching, Spectral Minutiae-based Matching, Recognition Accuracy/Performance, Matching/Comparison Speed, Memory Consumption.

CHAPTER ONE: INTRODUCTION

In this Chapter, an introduction to usage of computing systems is provided. It is noted that the use of ICT is on rise in a number of organizations and therefore introduces a new set of challenges. Some of the computer security challenges computing systems introduce are discussed as well as the traditional security methods that have been deployed to help in reducing the identified challenges. Fingerprint authentication is introduced as another method that could better reduce most of the mentioned challenges. Its advantages as well as challenges are also discussed paving way for an introduction to the concept of multiple enrollment fingerprint recognition. Multiple enrollment solves a number of challenges introduced by single fingerprints but also introduces more challenges. These are discussed in section 1.1.4, their summary made in section 1.2 (as the problem statement). Section 1.3 of this chapter provides the purpose of carrying out this research and its objectives while in Section 1.4, the research questions are formulated. The significance/benefits of the study are discussed in section 1.5 while the last section of this chapter presents the structure of the remaining part of the thesis.

1.1 Background

In the past, the usage of ICT and data processing equipment in organizations was at the lowest rate. The security of valuable/important and very sensitive/private information would be provided by physical and administrative means, for example, (physical) cabins/shelves with a combination lock, and (administrative) where prior research on people could be done before recruitment or hiring. Authentication of individuals would be by simple visual appearance, or physical explanations to prove identity [1].

Currently, ICT usage has increased worldwide among different organizations such as, hospitals, universities, schools, governments and many others; where electronic devices such as computers, tablets, iPads, mobile phones etc., are now the order of the day for digital communication instead of the old letter writing, digital money transfers instead of the old paper money forms, digital files (information) transfers and storage instead of the hard copy hand written documents kept in files and stored under key and lock cabins or safes. The electronic devices mentioned however need to be interconnected through networks (such as public telephone networks, data networks and internet) for them to allow easy access [2-9]. Organizations therefore have had to embark on designing computer networks that can ably support the above mentioned activities with ease.

1.1.1 Computer Security Challenges

The move towards ICT adoption or use of computing resources in organizations has brought about distributed/shared systems, use of networks, use of communication facilities and introducing a whole new set of organizational assets such as (i) physical assets like computers, network infrastructure elements, building hosting equipment, (ii) data e.g. electronic files or databases and (iii) software e.g. application software and configuration files. The assets named above contain valuable and sensitive information and therefore require tools that can provide adequate computer security to protect them against attacks on confidentiality, integrity and availability. It is practically difficult to see the individuals behind the computers and networks, of which these can be genuine users or attackers. Computer security needs to aim at challenges such as difficulty in authenticating individuals, software not being secure (it is not possible to design perfectly secure software applications to use), the internet and networks are not secure (day and night intruders are tapping, eavesdropping, carrying out traffic analysis etc.), the trust infrastructures used on the electronic devices are not secure themselves, and the individuals themselves being not secure.

Password usage is one of the commonest user authentication mechanism to computers (machines) that has been used for decades in various organizations. Other mechanisms that have been put in place are computer (machine) to computer (machine) authentication, which verify the computer identities but suffer no assurance of verifying the identity of the individual seated behind the computer. Tokens, smart cards, physical keys and many more have also been used for user authentication in many organizations; but have however suffered theft hence causing impersonation to individuals they were originally assigned to. Passwords are easy to create, easy to modify in case of compromise. However, passwords are easy to guess, searchable by an attacker (password dictionary attacks), they also require individuals to always remember them (users tend to write them on small papers, in wallets, for future reference), and to keep changing them. Those that are long and random are difficult for users to memorize; which is seen as an inconvenience [2-9]. It is important to note that more convenient mechanisms are needed to improve authentication of individuals to computers (machines).

1.1.2 Fingerprint Authentication

Many organizations now days have embarked on using biometrics to authenticate individuals and validate or verify their identities. Distinct from traditional identification methods, which rely on what you know (for example a PIN, a Password) or what you have (like a key, a token), a biometric system makes judgments based on what you are, and thus meets more stringent security requirements, while relieving users from the burden of remembering passwords [10].

A fingerprint possesses unique features that make it usable as a security measure for identification, authentication and verification of individuals; generally referred to as fingerprint recognition.

1.1.3 Advantages and Challenges with Fingerprint Recognition

The use of fingerprints as a biometric characteristic is one of the oldest and widely used method for recognition because of their high distinctiveness and high performance [10], [11]. For example, in the field of forensics, fingerprint recognition has been (can be) important in corpse and terrorist identification, criminal investigation, parenthood determination etc. Its application is also evident in the government (law enforcement) and commercial sectors most especially in the national identification cards, drivers' license, social security, boarder and passport control, computer network logon, ATMs and credit cards, physical access control, etc., to mention but afew [10], [12], [13], [14]. A number of factors are in favor of fingerprint usage; they are small, the capture devices are inexpensive, they are easy to collect, they are many (10 fingers) and available for collection, their recognition rates meet the needs of most of the applications, their acceptance by public is high, they provide reliable security and many others.

Fingerprint recognition has not only acquired a wide spread use but also triggers security concerns in terms of errors and its recognition performance. Fingerprint images are never of good quality, they suffer intra-class variations such as displacement, rotation, partial overlap, non-linear distortion, fingerprint pressure during scanning, skin condition, noise, feature extraction errors and many more, to mention but afew. These can negatively affect the recognition performance in fingerprint recognition systems. However, multiple enrollment can help improve the recognition performance in fingerprint recognition systems where fingerprints suffer the above challenges.

1.1.4 Multiple Enrollment Fingerprint Recognition

Enrollment using multiple fingerprint samples (multiple enrollment) is a solution that can help in extending the information of a single enrolled fingerprint image and also ensure the reliability of each fingerprint image [10]. Multiple enrollment can also improve the recognition accuracy of the fingerprint recognition system by lowering the error rates, allowing robustness by lowering the False Rejection Rates for low quality or worn-out fingerprint images and also make spoofing harder [10]. In multiple enrollment, the multiple fingerprint samples per individual can be collected in one session (with in the same period of time and day) or at multiple sessions for example after a difference of about two weeks' time or more. Multiple samples of the same finger or different fingers can be collected for enrollment, stored as templates and later used for verification during matching.

Acquiring accurate fingerprint images for recognition in a onetime capture is infeasible because not all the necessary and distinguishable fingerprint information may be collected. This can be due to a number of factors such as noise, errors in the feature extraction module, fingerprint displacement and rotation during the enrollment or capture stage, distortion, low quality fingerprint images, worn-out fingerprint images, partial overlap, finger pressure and skin condition [10], [15]; these decrease the recognition performance/accuracy and make it hard to relay on single enrollment where one fingerprint sample is collected per individual.

The above mentioned factors can lead to high false non matches where fingerprint impressions from the same finger (of an individual) are falsely rejected. They can also lead to high false matches for cases where fingerprint impressions from different fingers (of different individuals) are falsely accepted to be the same [16]. The high false non matches and high false matches bring about a poor performance in the entire fingerprint recognition system. More so, it would even be worse for fingerprint recognition systems that use single enrollment for fingerprint recognition; for instance if the singly captured fingerprint image falls under the fore- mentioned factors. However, with multiple enrollment in place, it is possible to acquire a better recognition performance through fusion of the multiple enrolled fingerprint impressions of each individual [10].

It is true that multiple enrollment can help in improving recognition performance in fingerprint recognition systems. At Master's Research project [17], the researcher already carried out a research to verify recognition performance improvement arising from multiple enrollment in comparison to single enrollment fingerprint recognition systems. Multiple enrollment was observed to outperform single enrollment in all the experiments. It was however realized that there was still a challenge in developing usable, acceptable, implementable and robust [18] multiple enrollment based fingerprint recognition systems (algorithms) that can match only high quality fingerprints amongst the many enrolled fingerprint samples, with a high matching speed, little memory consumption but still maintaining a high recognition accuracy. More so, most studied multiple enrollment based fingerprint recognition systems still had poor recognition accuracies. These identified gaps make it almost impossible to implement multiple enrollment based fingerprint recognition systems in real-world applications. On the other hand, most of the multiple enrollment based fingerprint recognition systems have been designed mainly based on minutiae approaches but not others such as correlation and pattern based approaches.

1.2 Statement of the Problem

Using multiple enrollment can improve recognition performance in fingerprint recognition systems; but there are several technical and operational challenges to implementing multiple enrollment based fingerprint recognition systems. Multiple enrollment based fingerprint recognition systems still have low recognition accuracies, poor matching speeds, and consume a lot of memory making it difficult to implement them in real world scenarios. Also, most of multiple enrollment based fingerprint recognition systems have been designed mainly based on minutiae approaches but not others such as correlation and pattern based approaches.

1.3 Purpose of the Study/Objective

The purpose of this study was to provide a novel multiple enrollment fingerprint recognition approach that further improves recognition accuracy, the matching speed and reduces memory consumption in multiple enrollment based fingerprint recognition systems.

1.3.1 Specific Objectives

The specific objectives of this study are to:

1. Investigate techniques that could be used for integration in the design of better multiple enrollment based fingerprint recognition systems
2. Design a novel approach to multiple enrollment based fingerprint recognition systems design.
3. Implement (simulate) a multiple enrollment based fingerprint recognition system from the approach.
4. Test and evaluate the approach for viability

1.4 Research Questions

The main research questions for this work are:

- ✓ What are the current approaches being used in designing multiple enrollment based fingerprint recognition systems? *This question is important to achieve research objective 1. Formative research was done to find out the state of the art in design of multiple enrollment fingerprint recognition systems. It was then possible to determine the techniques that were available for integration to formulate the proposed approach. This research question was also important in determining the challenges and requirements needed to design better multiple enrollment based fingerprint recognition systems.*

- ✓ How can the design of multiple enrollment based fingerprint recognition systems be improved to achieve better recognition accuracy/performance and matching speed, but reduce memory consumption? *This research question aims at achieving objectives 2, 3 and 4. After knowing the challenges and necessary requirements, it was then possible to design a novel approach that yields better multiple enrollment fingerprint recognition systems. The novel approach was designed and a multiple enrollment fingerprint recognition system implemented (simulated) from the approach to test and validate its efficiency and effectiveness.*
- ✓ How would a particular fingerprint matching method/approach affect the design of multiple enrollment based fingerprint recognition systems design in terms of recognition performance/accuracy improvement, matching speed improvement as well as reduction in memory consumption? *This question also aimed at achieving objectives 2, 3 and 4. There are three kinds of fingerprint matching methods one can implement in fingerprint recognition systems. This research question helped in determining which method(s) perform exceptionally when implemented in multiple enrollment fingerprint recognition systems. Knowing the best performing method(s) was important in formulating recommendations to designers of such systems. This process was still part of testing and evaluating the approach.*

1.5 Significance of the study (Benefits)

This study was significant in the following ways:

1. Firstly, this study provides a state of the art overview about multiple enrollment fingerprint recognition system and areas that require future research and development in the field. Performance data about the existing multiple enrollment fingerprint recognition

systems has been provided. This performance data can also be referenced or benchmarked for future research and development activities by other researchers in the same area of study.

2. This study is significant in providing novel multi-sample (multiple enrollment) algorithms that further improves the recognition performance, matching speed and reduces memory consumption in multiple enrollment based fingerprint recognition systems.
3. Results from the study provide insights and prior knowledge to developers, decision makers and users on which fingerprint matching methods to use for design or to select when implementing multiple enrollment fingerprint based recognition systems in real-world deployment situations.

1.6 Thesis Overview

This remaining part of this thesis is organized into seven chapters, with each chapter focusing on a different topic. Each chapter of the thesis builds on the work presented in earlier chapters. **Chapter 2** provides the literature review and theory, where the origin, history of use of fingerprints and their viability as a biometric trait as well as an account of the trends in the technological developments and advances in multiple enrollment for fingerprint recognition are discussed. **Chapter 3** describes the materials, methods and the implementations of a series of techniques for multiple enrollment fingerprint recognition. The datasets used, as well as data analysis are also presented. **Chapter 4** presents a spectral minutiae fingerprint recognition method where a new multiple enrollment algorithm with a better recognition performance using a new fingerprint representation (minutiae spectrum) is discussed. **Chapter 5** provides a novel recognition performance improvement approach that performs prior selection of good fingerprint image samples of an individual for matching to further improve recognition performance, reduce the matching speed as well as memory consumption. **Chapter 6** presents a non-minutiae fingerprint matching technique; Gabor filter-based approach, the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. This approach first extracts Gabor features from all input fingerprint image sample, creates column vectors of the extracted features, normalizes them to zero mean and unit variance and finally stores them with unique identifications (IDS). Direct matching then follows calculating the Euclidean distance between the two feature vectors originating from the two fingerprint samples to be compared. It is from this Euclidean distance value obtained that a matching score is computed and standardized. **Chapter 7** presents an enhanced/improved non-minutiae fingerprint matching technique; Combined Feature Level and Score Level Fusion Gabor filter-based approach, the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. The enhanced approach first extracts Gabor features from all input fingerprint image sample, creates column vectors of the extracted features, normalizes them to zero mean and unit variance and finally stores them with unique identifications (IDS). A random feature level fusion of the feature vectors generated from the different fingerprints is performed. Two feature vectors are concatenated and feature selection done in preparation for final matching/comparison. It is at this stage after feature selection that multiple enrollment and single sample verification is done. Direct matching then follows calculating the Euclidean distance between the two newly fused feature vectors originating from the two randomly fused feature vectors of the fingerprint samples to be compared. It is from this Euclidean distance value obtained that a matching score is computed and standardized. **Chapter 8** concludes the thesis, provides some recommendations as well as further extensions that can be made to this research.

CHAPTER TWO: LITERATURE REVIEW AND THEORY

This chapter provides the origin, history of use of fingerprints and their viability as a biometric trait. It provides an account of the trends in technological developments and advances in multiple enrollment for fingerprint recognition. Section 2.1 introduces the literature survey as well as the common terminologies as used under multiple enrollment. In section 2.2 through 2.3, the concept of biometrics is introduced paving way for the introduction of the basic idea of fingerprint recognition where the fingerprint characteristics that establish its viability as a biometric trait are presented and the concept of Multiple Enrollment for fingerprint recognition discussed. In section 2.4, a brief literature survey on the technologies or approaches developed for Multiple Enrollment for fingerprint recognition before 2004 is first conducted, paving way for a more extensive literature survey on the research trends from the year 2004 onwards. A number of research papers are examined with respect to approach methodology and experimentation results. In section 2.5, comparisons are made based on the recognition accuracies amongst the different approaches by various the researchers, literature synthesized, and challenges were identified. An overall analysis of the literature was done, remarks/discussions and conclusions made in sections 2.6 and 2.7.

2.1 Introduction

The need to improve security with regards to authenticating/identifying individuals in high computing environments/organizations spurs researchers to invest in biometrics technologies (security mechanisms) that are more secure and convenient. The most common one that has been widely deployed world-wide is fingerprint recognition [10]. However, acquiring accurate fingerprint images for recognition in a one-time capture is infeasible; because not all the necessary and distinguishable fingerprint information may be collected. Enrollment using multiple fingerprint samples (multiple enrollment) is a solution that can help in extending the information of a single enrolled fingerprint image, assure the reliability of each fingerprint image and also improve the recognition accuracy of a fingerprint recognition system by lowering the error rates, allowing robustness by lowering the False Rejection Rates for low quality or worn-out fingerprint images and also make spoofing harder. This literature review provides the research trend in the area of multiple enrollment as explained in the sections that follow.

2.2 Biometrics

A biometric system is an electronic implementation of automatic human recognition using body characteristics, such as ear, vein, DNA, face, fingerprint, iris, gaits and voice, which are collectively called biometric. The current demand for higher security and more convenient operations, for example in the cases of access control and personal data protection, has spurred intensive research, deployment and commercialization of biometric systems. Distinct from traditional identification methods, which rely on what you know (e.g. PIN, Password) or what you have (e.g. key, token), a biometric system makes judgment based only on what you are, and thus meets more stringent security requirement, while relieving users from the burden of remembering passwords [10].

A biometric systems operation mode is dependent on what design context the application is intended. The two biometric systems operation modes known are identification and verification. If the context of the application is identification, then the biometric system will operate in identification mode, otherwise if the context is verification, it will operate in verification mode [10]. To recognize an individual in the identification operation mode, there is no need for claiming an identity. The biometric system simply searches the templates of all users enrolled in the entire database to find a match. This is called a one-to-many kind of comparison and if the individual is enrolled in the system database, the recognition will be a success, otherwise, it will fail. However, on the other hand, for the verification operation mode, there is claim of an identity. The biometric characteristic data (e.g. fingerprint) of the individual claiming an identity is captured and compared with his or her previously captured template(s), which was previously stored in the system database. This is a one-to-one comparison and if there is a match, then it is true that the identity claimed belongs to the individual, otherwise, if there is no match, the system rejects the claim.

The use of fingerprints is evident in the field of forensics, fingerprint recognition has been (can be) important in corpse and terrorist identification, criminal investigation, parenthood determination etc. Its application is also evident in the government and commercial sectors most especially in the national identification cards, drivers' license, social security, boarder and passport control, computer network logon, ATMs and credit cards, physical access control, etc., [10], [12], [13], [14] to mention but a few. Fingerprint recognition has not only acquired a wide spread use but also triggers security concerns in terms of errors and its recognition performance.

A fingerprint has qualities that enable it to become a biometric. From an anatomical perspective, the fingerprint is composed of a pattern of ridge lines and valleys. These are represented by dark and bright lines respectively as illustrated in Figure 1. Furthermore, the ridge lines consist of other components called sweat pores. On the other hand, as the ridge patterns flow along the finger, (i) terminations can occur whereby the ridge curve simply ends or (ii) bifurcations can occur; whereby the ridge line path divides into two paths. It is these terminations and bifurcations (illustrated in Figure 1) of the ridge lines that make it possible to locate distinctive features called minutiae points [19], which are very important in the fingerprint matching exercise. The other features a fingerprint possess are (i) the whorl and arc as classified by Lee and Gaensslen in [20]; and (ii) the loop and delta; which are squares and tringles that work as regulator points where the ridge lines are enfolded [21].

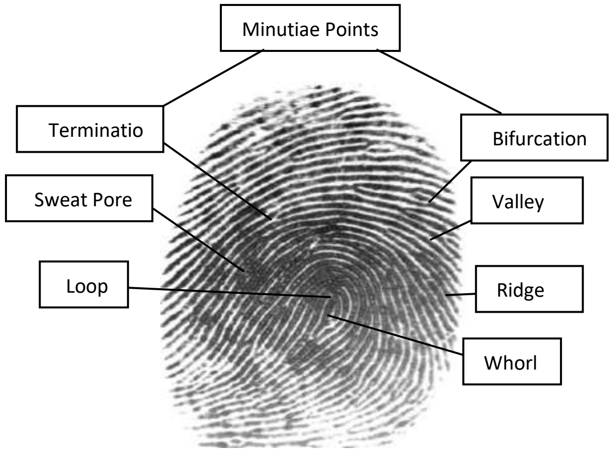

Figure 1: Anatomy of the Fingerprint

The deep complex structure and vast number of unique features gives rise to a wide variation of fingerprints among individuals; this guarantees sufficient differentiating capability of fingerprints in identifying people and impedance against spooling attempt. In addition, biometric research reports that the use of fingerprints as a biometric characteristic is one of the oldest and widely used method for recognition because of their high distinctiveness, high permanence, and high performance [10], [22]. The universality, distinctiveness, invariance to age, collect-ability and acceptability also jointly establish the candidacy of fingerprints as a biometric.

The viability of the fingerprint as a biometric is well demonstrated by practical applications. Historically, fingerprint, as a measure to distinguish individuals, was introduced as early as 1788 by Mayer [19]; where the anatomy of a fingerprint was described and a number of unique features acknowledged and characterized. However, the popularity of fingerprint was obscured until the ground breaking discovery of the uniqueness of fingerprint in 1880 by Henry Fauld [10], which, given the available technologies at that time, provided unparalled accuracy. Since then, developments and improvements in the fingerprint field continued; for example in 1888 where Galton [23] realized minutiae as other very important features for differentiating individual fingerprints. In 1899, Edward Henry also introduced the so called Henry system which was to classify fingerprints of different individuals [20]. For all that time, fingerprint had not been formally permitted as a valid personal identification not until the beginning of the twentieth century when it was approved and also included among the forensics analysis routine standards [20]. It is from the 1960s to 1969 when fingerprint identification began to transfer to automation and it's the same period when the Federal Bureau of Investigation fronted the idea of automating the fingerprint identification process. From the 1970s to the 1980s, fingerprint scanners for automation and technologies for digitization, image compression, image quality and classification, feature (minutiae) extraction and matching techniques were developed. From the 1980s onwards, advancements in fingerprint technology were seen. It is within this period when the so called M40 algorithm for FBI became operational. Not only that but also five Automated Fingerprint Identification Systems (AFIS) were deployed, another Integrated Automated Fingerprint Identification Systems (IAFIS) developed and made operational by 1999. Technology advancements in fingerprint identification continued until 2003 when the Fingerprint Vendor Technology Evaluation was instigated to evaluate how accurate fingerprint recognition systems were [24].

2.3 Fingerprint Recognition

In the twentieth century, a lot of research was conducted in the field of fingerprint recognition and it is when the technologies such as fingerprint classification, latent fingerprint acquisition, and fingerprint comparison were established [10]. At the same time, criminal fingerprint databases and investigation agencies (such as the FBI fingerprint identification division) were established [20]. It was within the same century that the current popular Automatic fingerprint recognition technology was established [10]

As time went by, new techniques were introduced to improve performance in fingerprint recognition systems. The fusion method of combining multiple biometric traits, or multiple instances of the same biometric trait, or complementary feature extraction and matching algorithms for the same instance of a biometric trait, was introduced to improve performance/accuracy in huge/sizable automatic identification systems [10]. With fingerprints, the fusion approach can take on five forms; (i) Combining other biometric characteristics like ear, iris, or face with fingerprints (multiple traits) [25], (ii) Combining multiple fingers (e.g. 2 0r 3 fingers) of the same person [26], (iii) combining multiple samples of the same finger (fingerprint information) acquired after using different sensors [10], (iv) combining multiple samples of the same finger [27]; where we have multiple enrolled fingerprint samples combined and (v) combining multiple representations and matching algorithms [28]; where diverse approaches to feature extraction and/or matching of fingerprints are combined.

Added to the above are other techniques that have been used/applied to further achieve better performance while using multiple enrollment in fingerprint recognition systems. Anil et al [29] classify fusion into different levels. First is the image level fusion technique which is mainly used when combining multiple images of the same finger. Second is the feature level fusion technique which is mostly used when combining multiple feature sets coming from the same finger. Third is the rank level fusion technique which is commonly used in identification systems to rank candidates in a templates database after a matching has been done. Fourth is the Score level fusion technique, which has commonly been used by many researchers due to its ability to combine information from all the sources as presented in the paragraph above. Last is the decision level technique which is mainly used to provide a final match decision. It also combines information from all sources as presented in the paragraph above. Our analysis shows that although it is possible to fuse multiple fingers at all the levels mentioned above, fusion at score level has been the most popularly used [30], [31] implementation level for multi-finger recognition systems.

2.4 Research Trends

With reference to Section 2.3 above, one approach that has often been applied to improve performance (matching accuracy) in fingerprint recognition systems is by fusion of multiple sources of biometric information with respect to multiple enrollment [10]. Not only that, but fusion with respect to multiple enrollment has been known to be important for cases where some of the fingerprint data is corrupted (e.g. due to certain reasons like finger displacement, finger rotation, non-linear distortion, partial overlap, fingerprint pressure and skin condition, noise resulting from remains or residue on the sensor platen coming from the previous fingerprint captures and lastly feature extraction errors). In such situations, other impressions of the same finger or different fingers could reliably be used for recognition.

As earlier mentioned, fusion can be carried out based on the information source chosen. The source of information we chose for fusion for this research was multiple fingers of the same person, where two or more fingers of the same person are combined. For this case of fusion, it is required to choose which fingers to be used from both hands and also in what order the users would present them at enrollment and verification. For example in the FVC2000 Fingerprint Verification Competition [15], up to four fingers were collected from each person; taking the forefinger and middle finger of both hands. The following order was used during the acquisition: first sample of left forefinger, first sample of right forefinger, first sample of left middle finger, first sample of right middle finger, second sample of left forefinger, second sample of right forefinger and so on, up to 8 samples per person. Huge performance improvements were realized by the different researchers in the competition.

Another good example regarding multiple fingers of the same person, is the SAS-DB2 fingerprint database (of University of Twente, Netherlands) that constitutes 12 samples per volunteer coming from six fingers; the pointing finger (or forefinger), middle finger and the ring finger of both hands. During the literature search it was noted that the ordering left-right first sample, left-right second sample and so on, have seemed to be the commonly used sequence during acquisition of multiple samples from the multiple fingers.

Fusion using multiple fingers of the same person, does not only achieve a higher recognition accuracy, but the fingerprint recognition system also becomes more difficult to fool [10]. For instance, during verification the user is often required to present his fingers in the same sequence as he did during enrollment. Based on the examples we have discussed above, this would not only require the intruder to get the four or six fingers, but also to know the correct sequence in which they should be presented at the fingerprint reader. This makes spoofing quite harder than when a single finger is used. Also on the other hand, if one of the samples from the given finger(s) is/are corrupted, the other(s) can reliably be used for recognition. Looking at the cases where feature level fusion is applied, it is also very difficult for an intruder to fool such a system. Fusion at score level has been the most popularly used [30], [31] implementation level for multi-finger recognition systems; although it is also possible to fuse multiple fingers at other levels. Recognition systems (mainly for identification) using multiple fingers have also mainly been deployed at border control and in the law enforcement agencies of different governments across the globe.

Fusion at score level entails combining the resultant matching scores into one to verify the truthfulness of a claimed identity. We chose it because among all the fusion implementation levels (fusion at feature-level, score-level and decision-level), it is fusion at score level that can easily be used in all the above mentioned biometric fusion scenarios. More so, it has been widely embraced and known to have the most significant tradeoff between effectiveness and ease of fusion [10]. Although implementation of fusion at score level seems more significant, the generated scores in some cases maybe non-homogenous hence requiring normalization. The most common techniques that have been used for normalization in fusion at score level are Sum Rule, Max Rule and Min Rule. The AND Rule, OR Rule and Majority Voting techniques are also commonly applied to better realize fusion at decision level [32]. It was however necessary for us to apply fusion at feature level in some experiments to achieve better results as presented in chapter seven of this thesis.

Research Studies from the late 90s; 1995 [33], 1997 [34], 1998 [35], [36], 1999 [37], [38], 2000 [39], 2001 [25], 2002 [28] and in 2003 [40], [41], [42], [43] have shown that a better recognition performance is attained when fusion of multiple sources of information is used than when a single source is used. This literature review mainly focuses on fusion using information from multiple fingers [26] of the same person; since it is one of the most commonly used and recommended for medium to large-scale automatic identification systems [10]. However, fusion using information from multiple samples of the same finger is also addressed in the survey, since multiple enrollment is also deployed.

Developments in multiple enrollment (with multiple fingers [26]) for fingerprint recognition started way back in the 20th century being evident in huge automatic identification systems like border control, law enforcement, background checks, voter registration system and many others. This approach was mainly introduced to improve recognition accuracy. This would not only improve performance but also balance cost, information content (by adding on to the little identification information from single fingers and single enrollment) and acquisition throughputs in large-scale automatic identification applications [10]. A number of researchers have reported that when two or more fingers of the same individual are joined, there is a great improvement in recognition accuracy.

Prabhakar and Jain [44] in 2001/2002 show that if different fingerprint matching algorithms are combined (four algorithms were used), the overall performance would be increase. Not only that, but they also show that combining multiple impressions or multiple fingers greatly improves the verification performance of the fingerprint recognition system. They carry out multiple enrollment by combining two fingerprint samples of the same finger or different fingers to verify the effectiveness of their proposed scheme. Their experiments were carried out on a database of 167 individuals (four impressions for each four fingers, 167x4x4 producing 2672 fingerprints) using minutiae-based matching and filter-based matching together with decision level fusion. Their results show that when multiple impressions or multiple fingers were combined, the recognition accuracy improved by more than 4% and 5%. The EER obtained after combination was 1.4%.

In 2003, Simon-Zorita et al [45] further supplemented the idea of Prabhakar and Jain [44] by proposing the storage of three fingerprint samples of the same finger at the time of enrollment. Verification would then follow by comparing the reference fingerprint sample with all the three stored multiple enrollment samples and choosing the maximum score to be the fusion score. A greater improvement in recognition performance was achieved.

To improve performance and robustness of a fingerprint matcher, in 2003, Luca and Fabio in [43] provided a perceptron based fusion technique whereby after enrollment, matching would take place with the help of multiple fingerprint matchers, which then generate a set of the multiple verification scores. It is these multiple scores that are input to the perceptron which later fuses them to have a maximum separation between the genuine users and the impostors. They used the FVC2000-DB1 containing 800fingerprint images. Minutiae based matching was performed and a great improvement in recognition accuracy was observed with EERs of 1.2%, 1.5% and 3.3% for the three experiments respectively. The 2003 FpVTE 2003 fingerprint algorithm benchmarking activity carried out by the National Institute of Standards and Technology (NIST) also reported that when more fingers of an individual were combined, the recognition accuracy greatly improved [46].

In 2004, the hybrid biometric systems like one in [47] which used the face and fingerprint as primary traits together with gender, ethnicity, and height as the soft characteristics, also showed a significant recognition performance improvement. Luca and Fabio in their 2004 research [48] fused multiple fingerprint sensors (optical and capacitive sensors) for fingerprint verification. Each sensor was subjected to fingers whose fingerprint images were captured; processed and distinguishable features (minutiae) extracted. The extracted feature sets were matched and two matching scores (each resulting from each sensor) are generated. It is these two scores that were combined to acquire a fused matching score. To attain a final decision, this score value would be evaluated based on a certain acceptance threshold, and a claimed identity would be accepted (as a genuine user) or rejected (as an impostor) if the score was above or below that acceptance threshold, respectively. A database of 20 individuals (with 1200 images) was used. A great recognition performance improvement of EER 2.2% was achieved after combining optical and capacitive matchers and using the Logstic-FD fusion rule. Other research Studies which show that a better recognition performance is attained when fusion of multiple sources of information is used than when a single source is used were in 2004 [49], 2007 [50], 2012 [51] and 2013 [52].

In their 2004 research, Ushmaev and Novikov [53] also report a great improvement in the recognition accuracy after using fingerprint data from multiple fingers. In the same year 2004, Lee, Choi, Lee and Kim [54] also report an improvement in the recognition accuracy after combining fingerprint data from two fingers. A database of 63 individuals (with each 20 fingerprint samples yielding 1260 total fingerprints) was used. Minutiae-based matching was carried out and score level fusion used to generate the final result. Wayman in 2004 [55] also carried out an evaluative research on the usage of fingerprint data coming from two or more fingers of an individual and a great recognition performance improvement was realized.

Umut, Ross and Jain [56] provide an automated template selection methodology that performs clustering to pick a template set which best characterizes the variability and typicality amongst the stored multiple fingerprint images. During the clustering process, a dendrogram which is in form of a binary tree whose nodes form clusters (representing fingerprint impressions), is outputted. It is from these clusters that the fingerprint samples with the minimum average distance from the other fingerprint samples are selected. Furthermore, the fingerprint samples are categorized basing on their average distance score in relation to other fingerprint samples and selection of those samples that display supreme likeness (those with the smallest average distance score) with all the other fingerprint impressions is done. With this technique, selection and ranking are based on Average Distance from the other impressions and then choose impressions with least average distance and uses minutiae as the fingerprint matching distinguishing feature. The experiments were carried out on a database of 50 different fingers with 200 impressions per finger an improvement in recognition performance was observed. EERs of 7.37% and 6.31% were obtained for the DEND method and MDIST method respectively.

The second NIST fingerprint algorithm benchmarking activity (NIST Proprietary Fingerprint Template (PTE) Testing) in 2005, also reported a rise in recognition accuracy when number of fingers were increased [57]. In their 2005 Study on Multi-unit Fingerprint Verification [58], Lee and colleagues also reported that the recognition accuracy was improved when fingerprint data from two fingerprints was used.

Chunyu and Zhou in 2006 carried out a comparative study of combining multiple enrolled samples for fingerprint verification [27]. Many schemes were studied which showed that there was always a greater recognition performance improvement when multiple enrollment was applied. They further proposed their own scheme which combined feature and decision fusion levels while using multiple impressions to obtain a far much better recognition performance. Minutiae-based matching was done and the databases used for the experiments were; THU (with 827 fingers and 8 impressions per finger yielding 6616 fingerprints), FVC2002 DB1 and FVC2002 DB2 [16]. A greater overall performance improvement in terms of FRR (0.0907) and FAR (7.97e-5) was observed with the proposed combination scheme.

In 2007 Lifeng Sha et al. [59] proposed a two-stage fusion scheme which uses multiple fingerprint impressions. They use a 2D wrapping model to transform all the multiple impressions and carry out a minutiae-based matching of the template fingerprint image with the reference fingerprint image. They use score level or decision level fusion to fuse the resulting scores from the different impressions to get a final result. All experiments were carried out on FVC2002 [16] database and a great improvement in recognition accuracy was achieved.

In 2009, Chunxiao, Yin, Jun, and Yang [60] in their research proposed a method that implements score level fusion using multiple fingerprint impressions for fingerprint verification to improve performance. Multiple samples of the same user's finger are enrolled and stored as templates for future reference. At the time of verification, the distance from the test fingerprint (claimed identity) and the centroid of reference fingerprints (stored templates) is computed in a multidimensional space. For comparability and matching, they measure the centroid of all the vertices for a given polyhedron and those vertices that are closer to the centre of the polyhedron are said to match better than all the others. The minutiae-based matching method is used to compare the reference fingerprint image and the stored template images and the distance output is later considered as the final score level fusion result. The FVC2000 DB1, FVC2000 DB2, FVC2002 DB2 and FVC2002 DB3 databases (of 100 individuals each with 8 impressions) [16] where used. Their results show a greater recognition accuracy is achieved when multiple enrollment with fusion was applied than in the uni-matcher. Equal Error Rates (EER) of 2.25%, and 5.75%, where obtained respectively.

To improve on recognition accuracy and reduce classification errors in biometric systems, Andres and Peter [61] in 2009 combined multiple instances of the same biometric, that is fingerprint and Eigenfinger and compare with the single instances. Minutiae and Eigenfinger features are extracted and stored as templates for future reference. For minutiae, matching of the stored templates then follows by a pair-wise execution generating a matching score for each comparison made. For matching with Eigenfinger, the mahattan-based classifier converts the Eigen distance measures into similarity scores. Minutiae and Eigenfinger score-level fusion is then performed to attain the final result. Two databases A (with 86 individuals and 443 samples) and B (with 31 individuals and 63hand images) were used. The processing time performance recorded for minutiae matching experiments was approximately 29-59 milliseconds (ms) per comparison, which resulted in a total average processing of about between 2478 - 5225 ms per identification. For Eigenfinger processing, it was reported to take about less than 1 millisecond (ms). A great recognition performance improvement was observed in multi-instance experiments than in the unimodal experiments. With minutiae experiments Equal Error Rates (EER) of 0.21% and 0.00% for database A and B were obtained respectively, while EER of 1.45% and 1.48% for database A and B were obtained respectively in the Eigenfinger experiments.

In their 2011 research, Mane et al [62] combined matching scores generated from multiple instances of the same finger acquired using the same fingerprint sensor. They used the score level fusion technique to attain a final recognition accuracy. The FVC2000 DB1, FVC2002 DB1, FVC2004 DB1 and their own BAMU (with 660x4 images) databases where used. They use the pattern-based matching method where a reference point and region of interest are first determined. Matching then follows after filtering the region of interest and computing the average absolute deviation (AAD). Their results show that there was a greater improvement in the recognition accuracy when multiple enrollment was applied than in single enrollment. Equal Error Rates (EER) of 13.7%, 12.0%, 44.5% and 3.00%, where obtained respectively as per the databases listed above.

Other non-minutiae based matching methods like the Gabor filter-based techniques in [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], were also seen to have attracted a lot of interest in designing fingerprint recognition systems. It was observed that the Gabor based fingerprint matching techniques were known to be rich in terms of distinguishing features and could be used as an alternative since they capture both the local and global details in a fingerprint. Their resultant representation is scale, translation and rotation invariant. They also produce short fixed length feature vectors, which makes them appropriate for indexing, faster fingerprint matching and storage on smaller devices [76]. From our analysis, it was however observed that the current research in using Gabor filter-based techniques had mainly focused on single enrollment rather than multiple enrollment for fingerprint recognition. It was also noted that there was little or no focus on the running time/speed as well as memory consumption while using the Gabor filter-based techniques. This research therefore ventures in performing experiments to determine the possibility of implementing Gabor filter-based techniques in multiple enrollment based fingerprint recognition systems taking into account recognition performance, running time/speed as well as memory consumption. A summary of the overall reported performances in the analysed literature is provided in Table 2.

Table 2: Summary of Performance Overview

Researcher(s)	**Matching Technique(s)**	**Size of Dataset(s)**	**Execution Time & memory used**	**Performance/recognition accuracy**
Lee, Choi, Lee and Kim(2004)	Minutiae-based technique	63 (20 samples each)	Not Reported	Not Reported
Umut, Ross and Jain(2004)	Minutiae-based technique with 2 methods, DEND and MDIST	50 (200 samples each)	Not Reported	DEND-EER (7.3%) and MDIST-EER (6.31%)
Chunyu and Zhou(2006)	Minutiae-based technique	THU-827 (8 samples each), FVC2002 DB1-110, and FVC2002 DB2-110	Not Reported	Overall FRR (0.0907) and FAR (7.97e-5)
Chunxiao, Yin, Jun, and Yang (2009)	Minutiae-based technique	FVC2000 DB1-110, FVC2000 DB2-110, FVC2002 DB2- 110 and FVC2002 DB3-110	Not Reported	EER (2.25%)
Andres and Peter (2009)	Minutia-based technique and Eigenfinger	A-86 (443 samples), B-31 (63 images)	Minutiae-based (between 2478 - 5225 ms per identification) and Eigenfinger (less than 1 millisecond	Minutiae-based (A-EER (0.21%) and B-EER (0.00%)), Eigenfinger (A-EER (1.45%) and B-EER (1.48%))

			(ms))	
Mane, Arjun V., Yogesh S. Rode, and K. V. Kale.(2011)	Pattern-based technique	FVC2000 DB1-110, FVC2002 DB1-110, FVC2004 DB1-110, and BAMU-660 (4samples each)	Not Reported	FVC2000 DB1-EER (13.7%), FVC2002 DB1-EER (12.0%), FVC2004 DB1-EER (44.5%), and BAMU-EER (3.00%)

2.5 Literature Synthesis, Challenges Identified and Overall Analysis

2.5.1 Literature Synthesis

Looking at the different categorizations; minutiae-based matching techniques and pattern-based matching techniques, and basing on the summary of the performance rates under each, that is; for minutiae-based matching techniques, we have, 7.3%&6.31%, 0.0907%&7.97e-5%, 2.25%, 0.21%&0.00%, 1.45%&1.48%, and, for pattern-based matching techniques, we have, 13.7%, 12.0%, 44.5%, and 3.00%, we make a comparison. From the above summaries, we notice that even though, there was some good accuracy rate of EER 3.00% in the pattern-based matching techniques, minutiae-based techniques exhibited better performances. This at first impressions would imply that, multiple enrollment for fingerprint recognition using minutiae-based techniques could perform better than the pattern based techniques. However, in our analysis, it was found out that only one research work [62] had carried out multiple enrollment for fingerprint recognition using the pattern-based technique.

A conclusive remark therefore about which technique outperforms the other could only be ascertained when more multiple enrollment experiments using pattern-based matching techniques were carried out. We also noted that amongst all the surveyed literature papers, one which reported almost the best recognition performance rates of 0.21% EER, 0.00% EER, 1.45% EER and 1.48% EER was based on relatively small sized databases, which could be considered less representative. This therefore implied that using a reasonably large database would be a reasonable basis to make better conclusions. Also, the venture into combining the two commonly used matching methods while using multiple enrollment for fingerprint recognition had not been given attention. Our assumption was that the recognition performance would greatly improve than basing on only one, although the execution time and memory consumption would be of concern. Finally, we also noticed that amongst all the surveyed papers, only one researcher reported the execution time taken and no research reported the memory consumption during the experimentations. From Our perspective, however good the recognition accuracy could be in multiple enrollment based fingerprint recognition systems, the execution time (aka speed) and memory consumption still remained a concern in the real world implementation. It was therefore important to address the two parameters to have better and reliable multiple enrollment based fingerprint recognition systems.

2.5.2 Challenges Identified

To enrich the understanding of the state of art of multiple enrollment for fingerprint recognition, it was important to know the challenges. We perform an overall sampling, identified some of the crucial challenges as well as provide some guiding recommendations.

One of the challenges cutting across was that local ridges of a fingerprint cannot be entirely categorised by minutiae [44]. This means that minutiae-based matching techniques do not utilize all the unique information exhibited in the ridge structure of fingerprints. In the same research, it was also realised that minutiae-based matching techniques are inferior in matching two or more fingerprint impressions with different numbers of unregistered minutiae points. In this case, pattern-based matching techniques would be sufficient in alleviating such problems since they capture both local and global features of fingerprints [77].

There was still a perception that it was only identification systems which should take into account both accuracy and speed since they have to explore the whole database to establish an identity. Therefore researchers have tended to concentrate more on them than verification systems. This is because, verification systems have often focused on accuracy since it is easy to meet response time because of the one-to-one comparisons. It was realized that many researchers in the literature survey had not considered execution time (aka speed) as an important issue yet multiple enrollment based fingerprint recognition systems perform a lot of many-to-many comparisons. With speed issues, user specific weights could help where by low weights are assigned to those images that are of poor quality and high weights to images with good quality based on certain parameters. With time these weights can be learnt and only considered during the multiple matching basing on a specific request set by the user. It is not only the recognition performance that would improve, but the matching speed as well reduction in memory consumption.

To our attention, it was realized that, it would also be important to further investigate under what conditions the recognition performance improvements provided by the multiple enrollment fingerprint recognition systems could justify the increase in system cost and user co-operation.

2.5.3 Overall Analysis

A lot of research that has been done relating to multiple enrollment has mainly focused on combining multiple fingerprint matchers (algorithms), like in [78], [43], [51], [60], [79], [44], and in some cases combining multiple fingerprint sensors, like in [48] to achieve better recognition accuracy; rather than concentrating on single fingerprint matchers focusing on multiple enrollment of fingerprints. Others like [56], [37], [34], [47], [35], [33], [40], and [41], focused on fusion of multiple sources of information to improve recognition performance. Researchers in [80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91], and [92] have instead used other fingerprint images enhancement techniques to improve recognition performance. From the analysis of the previously done research related to multiple enrollment, some of the researchers had implemented decision level fusion in fingerprint verification; whereas the majority had implemented score level fusion and others had tried to combine the two in some cases. From the literature searched, it is evident that there is a lot of interest in combining multiple sources of biometric information to improve the recognition accuracy.

However, on top of the avenues for improving recognition accuracy, little research concretely concentrated on improving the matching speed of such multiple source based biometric systems, usability, memory consumption and acceptability. Although multi-modal, multi-sensor, multi-matcher/algorithm based fingerprint recognition systems somehow improve the recognition performance, their implementation, usability, high memory consumption, poor matching speed and acceptability in real-world deployment situations still remains a challenge; it would require more costs to acquire the necessary extra computational resources, to implement as well as convincing and training users to adapt to them. The analyzed recognition accuracies from the current researches are also still low. Also according to our analysis, researchers have not concretely recommended which fingerprint matching methods work best when multiple enrollment is deployed in real world applications.

2.6 Remarks/Discussions

In this literature survey, developments in multiple enrollment for fingerprint recognition technology over the past twenty years has been presented, hoping to give a comprehensive account of the state of the art in the field. It can be concluded from the comparative assessment of the different approaches that, the performance of multiple enrollment fingerprint recognition systems has continuously improved with a lot of technology advancements over the years.

At the same time, approaches for implementing multiple enrollment for fingerprint recognition are more diversified compared with the situation in the 20th century, with minutiae-based matching techniques generally giving a better recognition accuracy, but being more inferior in matching two or more fingerprint impressions with different numbers of unregistered minutiae points, as well as not being able to entirely categorize local ridges of a fingerprint. Our analysis has revealed that combining both minutiae and pattern-based matching techniques while deploying multiple enrollment would have a significant influence on the recognition result, but devising a fast algorithm to ameliorate the time consuming computation and memory consumption would be a pre-requisite for such multiple enrollment fingerprint recognition systems to gain real world implementation and commercial popularity.

At the moment, the lack of taking into account the computation time and memory consumption visa-vee recognition accuracy is one of the challenges facing multiple enrollment recognition systems; papers include experimental results that are based mainly on accuracy. Also, not every paper states explicitly under what conditions the recognition performance improvements provided by the multiple enrollment fingerprint recognition systems could justify the increase in system cost and user co-operation, making a thorough comparison impractical and obstructing identification of the best approach.

The analysis and gaps presented in the section above spur new research directions in the area of multiple enrollment for fingerprint recognition. A closer study on the existing fingerprint biometric systems that use multiple sources of biometric information (concentrating mainly on multiple samples of fingerprints from many fingers of the same individual) to evaluate their performance (recognition accuracy), matching speed, acceptability, usability, and memory consumption was important.

This study provides a novel multiple enrollment fingerprint recognition approach that further improves recognition accuracy, the matching speed and reduces memory consumption in multiple enrollment based fingerprint recognition systems. This approach also focuses on performance and accuracy evaluation of both minutiae-based and pattern-based fingerprint matching methods to realize which method performs exceptionally when multiple enrollment is deployed. Rather than using multiple matchers, multiple modals, or multiple sensors; a single matcher, sensor and modal is used to allow for acceptability, usability and easier implementation.

2.7 Conclusions

Our literature review analysis shows that a lot of research that has been done relating to multiple enrollment had mainly focuses on combining multiple fingerprint matchers (algorithms) to achieve better recognition accuracy; rather than concentrating on single fingerprint matchers focusing on multiple enrollment of fingerprints. However, the urge to combine multiple sources of biometric information to improve recognition accuracy has been observed to have continuously and periodically increased through the two decades. It has been noted that some of the researchers have implemented decision level fusion in fingerprint verification; whereas the majority have implemented score level fusion and others have tried to combine the two in certain cases. In the literature survey, few researchers implemented feature level fusion in multiple enrollment based fingerprint recognition systems. The literature survey also shows that the analyzed recognition accuracies from the different researchers are still low, little research has concretely concentrated on improving the matching speed (execution time) of such multiple source based biometric systems, the usability, memory consumption as well as acceptability. It was also noted that researchers had not concretely recommended which fingerprint matching methods would perform best when multiple enrollment was deployed in real world application scenarios. The literature survey indicates that there is need for closer studies on the existing fingerprint biometric systems that use multiple sources of biometric information (concentrating mainly on multiple samples of fingerprints from many fingers of the same individual) to evaluate their performance (recognition accuracy), matching speed, acceptability, usability, and memory consumption. It also indicates that there is need to develop novel multiple enrollment fingerprint recognition approaches which can further improve recognition accuracy, the matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems. Analysis of other matching methods rather than only minutiae based ones was also an important way forward made.

With respect to research question one of this thesis that was formulated in Section 1.4, this Chapter addresses objective number one by providing a state of the art survey of multiple enrollment for fingerprint recognition. All the existing approaches that have been used in designing multiple enrollment based fingerprint recognition systems are provided, challenges discussed and way forward made. These were important to derive requirements for answering research question two to achieve the remaining research objectives as formulated in Section 1.4. The contribution of this Chapter is a literature review survey that serves as a quick overview of the state of the art in multiple enrollment for fingerprint recognition for the past two decades.

CHAPTER THREE: MATERIALS AND METHODS

This Chapter provides an introduction to the most commonly used fingerprint matching methods, as well as introduces the design science research methodology which was followed while carrying out the entire research. In section 3.2 the research approach is presented while section 3.3 provides a deeper description of how the research was designed. Section 3.4, provides a description of the whole research process undertaken following the Design Science approach steps. It is in this section where, a description of the datasets, how the fingerprint databases were identified, and full descriptions of the databases are provided, how the data was analysed, the matching methods used, experimental setup, the recognition performance, execution/running time (aka speed) and memory measurements, the testing strategy as well as the implementation environment of all the experiments are explained.

3.1 Introduction

This study adopts the design science research methodology in [93]. The design science methodology research approach whose main goal is to create or contribute to new and interesting design science knowledge in a chosen area of study has been widely used. By creation of knowledge, the methodology focuses on design of novel or innovative artifacts for examples algorithms, human or computer interfaces and systems. The approach mainly uses mathematical and computational methods to evaluate the quality and effectiveness of the designed artifacts; in some cases empirical methods are used. This research/study focuses on the design of an approach with improved algorithms based on existing ones for better implementation of multiple enrollment based fingerprint recognition systems in real world applications. The effectiveness of the theoretical approach to designing multiple enrollment based fingerprint recognition systems has been evaluated through design (simulation) of an artifact. This therefore qualifies the design science research approach as appropriate in the context of this research.

Two main fingerprint matching techniques, (i) the pattern-based matching method as presented in [22, 94, 95] and the minutiae-based matching method as discussed in [10] have been tested to check their suitability in terms of recognition performance, computational speed/running time and memory consumption when multiple enrollment is deployed in real systems. These techniques have been chosen for use in this research because of their popular use [10, 95]. Based on the information above, the research focuses on four key areas; the matching technique used (Pattern-based Matching technique or Minutiae-based Matching technique), the size of dataset(s) on which the experiment are done, the execution time (aka speed) and memory used, as well as the performance/ recognition accuracy attained.

In the minutiae-based matching techniques, after acquiring the fingerprint image sample, minutiae are extracted, stored as sets of points in a two dimensional plane and matching follows by determining the alignment between the template and the input minutiae sets which yield in the uttermost number of minutiae pairings. During literature analysis, it was found out that the minutiae-based matching techniques were known to be the most common and widely used fingerprint matching method [10, 95].

In the pattern-based matching methods, the fingerprint image samples are acquired/captured and their templates stored in a database. Matching then follows by comparing the basic fingerprint patterns such as the arch, whorl, delta and loop; between the previously stored template and a candidate fingerprint. To achieve a desired output, it requires that the images be aligned in the same orientation. For this to happen, the algorithm has to find a central point in the fingerprint image and focus on that. The stored template contains the type, size, and orientation of patterns within the aligned fingerprint image. During matching, the candidate fingerprint image is graphically compared with the template to determine the degree to which both of them match and a match score is generated [22,94,95].

The design science research method was used to first find out more information about the chosen matching methods and to better understand the problem as well as test the theoretical concepts. The reason it was deployed was to find a clear basis for a more conclusive research and be able to draw conclusions about the requirements that were needed in structuring the approach. Different prototype multiple enrollment based fingerprint recognition systems (algorithms) were developed (simulated) as the novel artifacts to implement the approach. The methodology has been important in verifying the new approach to designing multiple enrollment based fingerprint recognition systems. It was inadequate to simply assume that the theoretical approach to designing multiple enrollment based fingerprint recognition systems would produce expected results without practical verification (simulation). It is for this reason therefore as to why the design science methodology was used; since practical development of an artifact is part of it.

3.2 Research Approach

The gaps presented in Chapter two were a driving force to this research; where a closer study was done on the existing biometric systems (mainly fingerprint biometric systems) that use multiple sources of biometric information (concentrating on multiple samples of fingerprints of the same individual like in [56], [27] and [96] to evaluate their performance (recognition accuracy), matching speed, acceptability, usability, and memory consumption.

This research study presents a novel multiple enrollment fingerprint recognition approach that further improves the recognition accuracy, the matching speed and reduces memory consumption in multiple enrollment based fingerprint recognition systems in two main ways.

Firstly, this approach focuses on image selection prior to matching by automatically assigning/allocating a certain weight. During fingerprint matching, when a poor quality fingerprint image is found; a low weight value is assigned and when a good quality fingerprint image is found; a high weight value is assigned. This implies that it is only those fingerprints assigned a high weight value that are chosen during the matching (fusion) process to improve the recognition accuracy, matching speed as well as reduce on memory consumption. Score level fusion has been implemented to generate final results.

Secondly, it experiments the use of a non-minutiae matching method (Gabor filter based) with incorporation of feature level fusion and score level fusion to attain better results.

The approach mainly focuses on recognition performance, matching speed and memory consumption evaluations of both minutiae-based and non-minutiae based fingerprint matching method (Gabor filter based) to realize which method perform exceptionally when multiple enrollment is deployed. Rather than using multiple matchers, multiple modals, or multiple sensors; a single matcher, sensor and modal (multiple fingerprint samples) have been used to allow for acceptability, usability and easier implementation.

3.3 Research Design

To better realize the effectiveness of the approach to designing multiple enrollment based fingerprint recognition systems, all experiments have been compared with the existing reported multiple enrollment based fingerprint recognition systems. From this perspective, the research study first carried out a formative research on most of the existing reported multiple enrollment based fingerprint recognition systems, performed multiple enrollment experiments based on the identified databases, and later compared the findings/results with those of the existing multiple enrollment fingerprint recognition systems in literature. With this, it has been possible to identify variations and make concrete performance evaluations which have generated appropriate arguments for recommendations on how to better design multiple enrollment based fingerprint recognition systems. The next Section 3.4 provides a description of the whole research process undertaken following the Design Science approach steps.

3.4 The Design Science approach

The Design Science approach takes on five steps of which this research study followed as explained below:

3.4.1 Step1: Awareness of the problem.

It is at this stage that the challenge or problem was identified to derive formulation of a better approach or solution. The first task was to find out more information about the chosen matching methods and to better understand the problem as well as testing our concepts. Different methods were studied as well as literature searched for a good benchmark and kick off. This was done to attain a more conclusive research. A thorough formative research analysis was done to help draw conclusions on what requirements were needed in structuring the approach. In the problem statement section, the study identifies the challenges/problems at hand and presents an approach to designing multiple enrollment based fingerprint recognition systems in a better way. It is in this phase that the multiple enrollment based fingerprint databases are identified as explained below.

3.4.1.1 Fingerprint Image Database Identification

In this study, it was necessary to identify the fingerprint databases to use while setting up the different experiments. In this process, certain qualities were considered important to identify the suitable databases to use: (i) whether the database consisted of multiple enrolled fingerprint image samples, (ii) whether it was large enough and well representative (heterogeneous), (iii) whether it had commonly been used internationally in the Biometrics research field, and (iv) that it should not be too old (preferably not more than 15years old). This process was important in this study before conducting any analysis. Some example existing international commonly used fingerprint databases that were identified were: UPEK Fingerprint Database, SAS-DB database, CASIA Fingerprint Image Database, FVC 2006, FVC 2004, FVC 2002, FVC 2000, MCYT-Fingerprint 100, ATVS, Biometrix, Neurotechnologija, and Innovatrics. It was from the above list that the suitable databases (SAS-DB2, FVC 2000 and FVC 2006) as per the desired qualities were identified. Once the databases were identified and known, organized and data stored, the sample size to use for the experimentation setup was then determined based on the size of the databases. A full description of each of the chosen fingerprint databases above and the sample size taken is provided in the next section.

3.4.1.2 Database Descriptions

Descriptions of the databases identified are presented. Two public (internationally known) fingerprint databases namely; FVC2000-DB2 [15] and FVC2006-DB2 [43], were used for all experiments in Chapter five to seven. Experiments in Chapter four were carried out using both the FVC2000-DB2 [15] and the SAS-DB2 Database.

A. The FVC2000-DB2 Database

This database comprises fingerprint image samples taken from 110 people with 8 impressions per person generating a total of 880 fingerprints. These multiple samples were collected from untrained people, there were no attempts made to guarantee the least possible acquisition quality and the collection was done in two different sessions. However, for all experiments in this research, set A (FVC2000-DB2-A of 100 individuals) of the whole database which contains a total of 800 fingerprints was used.

B. The FVC2006-DB2 Database

This database comprises fingerprint image sample taken from 150 people with 12 impressions per person generating a total of 1800 fingerprints. During the collection of fingerprints, there was no deliberate introduction of difficulties such as exaggerated distortion, large amounts of rotation and displacement, wet/dry impressions, etc. (as it was done in the previous editions), but the population in this database is more heterogeneous and also includes manual workers and elderly people. However, the final datasets were selected from a larger database by choosing the most difficult fingers according to a quality index, to make the benchmark sufficiently difficult for a technology evaluation. For all experiments in this research, subset A (FVC2006-DB2-A of 140 individuals) with a total of 1680 fingerprints images was used.

C. SAS-DB2 Database Description

This database is owned by the Signals and Systems (SAS) group at the Faculty of Electrical Engineering Mathematics and Computer Science (EEMCS) of the University of Twente in the Netherlands. The database consists of fingerprint images taken from 123 people with 12 samples per person collected from 6 different sessions and they are in resolution of 500 dpi. The U.are.U (by Digital Persona) optical sensor was used to collect the fingerprint images of this database. Up to six fingers were collected for each volunteer; the pointing finger (or forefinger), middle finger and the ring finger of both hands. There were several minutes in between after every two captures and for most persons, there was an interval of about three to five weeks between the two recordings. The images were acquired from untrained people and there was no systematic cleaning of the sensor platens after each acquisition. For all the experiments in research under chapter four, we used fingers numbered from 1 to 100, with 12 samples per finger and we used all the 12 samples from each finger.

The result of this phase was a literature review survey which included the research trends in multiple enrollment fingerprint recognition systems, the challenges/problems at hand, the chosen multiple enrollment based fingerprint databases and sample size to use, a list of laboratories working on fingerprint recognition (multiple enrollment) and requirements that were needed for us to be able to formulate a different and better approach to multiple enrollment fingerprint recognition systems design. This phase was important in answering the first research question, achieve the first objective as well as guide research question two and research objective two.

3.4.2 Step2: Suggestion.

In this step, a noble solution/approach either an improvement (new solutions for known problems), invention (new solutions for new problems) or exaptation (non-trivial extension of known solutions for new problems) to address the challenge or problem is formulated. In the context of our study, improvement was applicable since a new solution to a known problem was proposed. The result of this stage was the proposed approach to multiple enrollment fingerprint recognition systems design as discussed in the section below.

3.4.2.1 The Multiple Enrollment Fingerprint Recognition Approach Design

After designing the approach which is provided in Section 3.2, a multiple enrollment based fingerprint recognition algorithm was implemented and then used the existing methods to carry out the experiments. Different comparisons were done based on the database chosen. For the different databases containing a certain number of fingers with a given number of samples per finger, each comparison was done based on a number of fingerprints that were selected from the dataset; with some as the *reference* fingerprints and others as the *test* fingerprints. Score level fusion based on the Max Rule in [32] then followed by taking the maximum score amongst the attained values, was performed. In some case, feature level fusion was deployed.

Two categories of multiple matching were carried; (i) Multiple Genuine Pair Matching and (ii) Multiple Impostor Pair Matching.

In multiple matching category (i), a certain number of fingerprints of the same person each as a *reference* were chosen matching each of them with a selected sample of that person as the *test* fingerprint. For any given image samples per person, relative permutation sets for multi-sample enrollment and single-sample verification were established. There was no specific criteria for formulating these permutations; to allow for robustness, it was randomly done.

In multiple matching category (ii), a sample of an identity (individual) in a given database was chosen and matched with the selected multiple enrollment samples of the different identities (individuals) of the same database.

This phase helped in answering the second research question, achieve part of the second objective as well as guide research question three and research objective three and four.

3.4.3 Step3: Development.

From the designed approach in step 2 above, an artifact was implemented (simulated) and later used to check the viability of the designed approach. Different prototype multiple enrollment based fingerprint recognition systems (algorithms) were developed (simulated) as the suggested novel artifacts to implement the proposed approach. In this step therefore, the proposed solution was actualized and implemented as explained in the section below

The result of this phase was an artifact representing a multiple enrollment fingerprint recognition system. This step therefore helped us answer to research question 2 and 3 as well as achieving objectives 3 and 4.

3.4.4 Step4: Evaluation.

After developing the artifact, it was at this stage that experiments were set up, data analyzed, processed and the performance, speed and memory consumption of the algorithms tested and evaluated as explained in the Section 3.4.4.1 through Section 3.4.4.6. We could not simply assume that our theoretical approach to designing multiple enrollment based fingerprint recognition systems would produce expected results without practical verification (simulation). This phase's results were recognition performance (accuracy) checks, matching speed checks, memory consumption checks, minutiae based methods and non-minutiae based method comparisons. A description of the activities done under this phase is provided in the section below

3.4.4.1 Data Analysis

The data was first studied, described, and models made and later analyzed it using both the pattern-based matching methods [22], [94], [95] focusing on the arch, whorl, and loop as the fingerprint matching features and the minutiae-based matching method (in particular as Traditional minutiae-based matching [97], Spectral Minutiae-Based Matching [98] etc.) using minutiae points as the fingerprint matching features during the analysis. These methods/techniques were chosen for implementation in this research because of their popular use [10], [95]. These methods have also been known for better performance in the fingerprint recognition field. Not only that, but they are also quite easy to understand as well as to implement in fingerprint recognition systems. The next section provides a description of the methods that were used.

3.4.4.2 Matching Methods Used

This section presents a description of the matching methods used throughout all the different experimentations in this research.

A. Traditional Minutiae-based matching

In this method, a commercial minutiae matcher Verifinger 6.0.0.7 was used for the multi-sample fingerprint enrollment and single-sample verification. Verifinger was chosen for use so that a realization of the fingerprint recognition performance and evaluations resulting from multiple enrollment in the commercial perspective is attained. The fingerprint image samples of the ID(s) to be matched are loaded to Verifinger which extracts the minutiae templates and stores them with unique names. With help of the Verifinger matcher and depending on which samples to match/compare, direct matching is done between the stored minutiae templates of the enrollment samples and those chosen for verification. A matching score is generated and stored in a file for later use. For more information about the usage of Verifinger for fingerprint recognition and other capabilities, readers are referred to [97].

B. Spectral Minutiae-based matching

In this method [98], all the minutiae template sets from the fingerprint image sample are first extracted and then stored with unique identification (ID) names. The extracted minutiae sets are then transformed into a spectral minutiae form (referred to as Minutiae Spectrum) by representing them as a fixed-length feature vector which is invariant to translation. Within the minutiae spectrum form, rotation and scaling also become translations which can easily be compensated for. Once the transformation into a Spectral Minutiae representation is done, direct matching follows by correlation between the two Spectral images and a similarity score is generated.

C. Gabor Filter-based matching

For this method, the Gabor features of all input fingerprint image samples are first extracted like in [99]. Column vectors consisting of the Gabor features of the input fingerprint image samples are created. These feature vectors are normalized to zero mean and unit variance (to remove any noise originating from sensors as well as the grey level background which maybe generated because of the finger pressure differences), and then stored with unique identification (ID) names. Direct matching follows by calculating the Euclidean distance (see Equation 1-*Eq*1) between the two feature vectors; *Fvec1* and *Fvec2* respectively originating from the two fingerprint samples to be compared. Based on this Euclidean distance(*Ed*) value attained, a matching score is computed such that; the higher the Euclidean distance(*Ed)*, the lower the matching score and vice versa. The score is computed and standardized as in [100].

3.4.4.3 Experimental Setup

This section describes the setup of both the minutiae-based and Gabor filter-based multiple enrollment experiments as used in chapter five to seven. The setup of the single enrollment experiments carried out in chapter four is also presented.

1. The Single Enrollment Experimental setup

In this experiment, each comparison was done based on two fingerprints that are selected from the dataset; with one as the reference fingerprint and the other as the test fingerprint. This experiment was carried out in chapter four. The description of the genuine and impostor pairs were as follows:

A. Genuine Pairs

For single genuine pair matching, all the possible combinations were used; matching each of the other samples (*test* fingerprints) of the same person with the first fingerprint sample of that person as the *reference*.

B. Impostor Pairs

For single impostor pair matching, one sample (the first) was chosen from each identity in the database. The single enrollment experiments were included as part of this research to provide a basis for making a comparison and an evaluation of the multiple enrollment experiments, with regards to the recognition performances achieved.

2 The Multiple Enrollment Experimental setup

Based on the database, different comparisons were performed during the experimental setup. In the FVC2000-DB2-A database which comprises 100 fingers with 8 samples per finger, each comparison was performed based on five fingerprints that were selected from the dataset. In this case, four of the five fingerprints were used as the *reference* fingerprints and one as the *test* fingerprint. Score level fusion based on Max Rule in [32] then followed by taking the maximum score amongst the four attained values. In the FVC2006-DB2-A database which comprises 140 individuals with 12 samples per finger, each comparison was performed based on seven fingerprints that were selected from the dataset. For this case, six of the seven fingerprints were used as the *reference* fingerprints and one as the *test* fingerprint. For the SAS-DB2 database which comprises 123 individuals with 12 samples per finger, six fingerprints of the same person each as a reference were also chosen, matching each of them with the seventh sample of that person as the test fingerprint. For the 12 samples per individual six permutation sets, Set1, Set2, Set3, Set4, Set5 and Set6 for multi-sample enrollment and single sample genuine verification were established. Again, Score level fusion based on the Max Rule in [32] then followed by taking the maxi/mum score amongst the six attained values. Below is a description of the genuine and impostor pairs used for the multiple enrollment experiments.

A. Genuine Pairs

For multiple genuine pair matching in the FVC2000-DB2-A database, four permutation sets (shown in Table 3), Set1, Set2, Set3 and Set4 were established for multi-sample enrollment and single-sample verification. Based on the 8 samples per person, four fingerprints of the same person, each as a reference were chosen matching each of them with the fifth sample of that person as the test fingerprint. On the other hand, for multiple genuine pair matching in FVC2006-DB2-A and SAS-DB2 database, six permutation sets (shown in Table 4), Set1, Set2, Set3, Set4, Set5 and Set6 were established for multi-sample enrollment and single-sample genuine verification. Based on the 12 samples per person, six fingerprints of the same person each as a *reference* were chosen, matching each of them with the seventh sample of that person as the *test* fingerprint. There was no particular procedure followed in creating the permutation sets. All the permutation sets were randomly formulated.

A. Impostor Pairs

For multiple impostor pair matching in FVC2000-DB2-A database, the first sample of an identity in the database was chosen and matched with the four multiple enrollment samples of the different identities. While for multiple impostor pair matching in FVC2006-DB2-A and SAS-

DB2 database, the first sample of an identity in the database was chosen and matched with the six multiple enrollment samples of the different identities.

Table 3: FVC2000-DB2-A database permutation sets of the impressions used for multi-sample enrollment and single-sample verification

Permutation Sets	Enrollment Samples	Verification Samples
Set1	1,2,3,4	5,6,7,8
Set2	1,3,5,7	2,4,6,8
Set3	1,2,7,8	3,4,5,6
Set4	1,5,6,7	2,3,4,8

Table 4: FVC2006-DB2-A and SAS-DB2 database permutation sets of the impressions used for multi-sample enrollment and single-sample verification.

Permutation Sets	Enrollment Samples	Verification Samples
Set1	1,2,3,4,5,6	7,8,9,10,11,12
Set2	1,3,5,7,9,11	2,4,6,8,10,12
Set3	1,2,3,10,11,12	4,5,6,7,8,9
Set4	1,7,8,9,10,11	2,3,4,5,6,12
Set5	1,3,5,8,10,12	2,4,6,7,9,11
Set6	1,6,7,8,9,10	2,3,4,5,11,12

3.4.4.4 Recognition Performance, Execution time (Speed) and Memory Measurements

It was important to measure how correctly the new approach to multiple enrollment fingerprint recognition system design would accurately match the fingerprints originating from the same individual but avoid incorrectly matching fingerprints originating from different individuals.

This study focused on the following accuracy indicators for comparisons: False Acceptance Rate (FAR); the probability of a false match error happening, False Rejection Rate (FRR); the probability of a false non-match error happening and the Equal Error Rate (EER); one where the

FAR and FRR become identical (equivalent). In our accuracy indicators, we considered use of percentages basing on the data we generated from the experiments. The genuine and Impostor Detection Error Tradeoff (DET) curves [101] were also used to compare the performances of the multiple enrollment fingerprint recognition systems.

The processing time, template size as well as the memory consumption were also used as performance indicators in this study. The running time was measured based on the MATLAB Elapsed Time (etime) function which calculated the time taken for the algorithms took to complete a task. To measure memory consumption, the MATLAB Profiler feature was used to monitor the peak memory consumption/usage for each algorithm during all the experimentations. To better realize the effectiveness of the approach, the experimental results were compared with the existing multiple enrollment based fingerprint recognition systems.

3.4.4.5 Implementation Environment

All the methods and algorithms in Chapter four were implemented in MATLAB R2010a. All the experiments were performed on an Intel(R) Pentium(R) D CPU 2.80GHz with 2.00GB of RAM running a 64-bit Windows 7 Enterprise Operating System and the Verifinger 6.0.0.7 extractor [97] was used to extract the minutiae templates from all the fingerprint images in both databases.

On the other hand, the experimentations and algorithms in Chapter five to seven were all implemented in MATLAB 7.12.0 (R2011a). All the experiments were carried out using an Intel(R) Core(TM) i5-3230M CPU 2.60GHz, with 4GB of RAM running a 64-bit Windows 8 Pro operating system. For the minutiae-based method, the VeriFinger 6.0.0.7 extractor was used to extract all the minutiae templates from all the fingerprint images in all the two databases. For the Gabor Filter-based method, the Gabor filter extractor in [99] was used. The MATLAB Elapsed Time (etime) function was used to calculate how long the algorithms took to complete a task from the start to the end. The MATLAB Profiler feature was used to monitor the peak memory consumption/usage for each algorithm (Minutiae-based and Gabor filter-based) during all the computations/experimentations.

3.4.4.6 Testing Strategy

The approach was tested by performing comparisons amongst the genuine recognition attempts and the impostor recognition attempts to determine the improvements in the recognition accuracy, speed and memory consumption reduction. All the testing was done at the researcher's site using the researcher's hardware. All experiments and evaluations were done in a fully controlled environment so that all input and output processes were thoroughly monitored. For practicality reasons in our testing strategy, we tried to enforce a limit on the maximum response time of the algorithms in the approach for enrollment and comparisons. The testing strategy discussed above helped in monitoring and evaluating all the speed (processing time), recognition performance/accuracy as well as memory consumption indicators as already discussed above.

The phase helped in answering research question 2 and 3 as well as achieving objective 3 and 4 of this research.

3.4.5 Step5: Conclusion.

After carrying out all the experiments, conclusions were drawn and reported as explained in the proceeding chapters. The outputs of this phase were a series of write-ups in form of research paper findings as well as a final PhD Thesis.

CHAPTER FOUR: SPECTRAL MINUTIAE FINGERPRINT RECOGNITION

This chapter introduces the concept of multiple enrollment for fingerprint recognition to determine its viability and effectiveness in fingerprint recognition systems. An evaluation of multiple enrollment in comparison to single enrollment and other existing multiple enrollment research is done. The Chapter first introduces the concept of biometrics and the challenges associated with single enrollment as well as acquiring multiple fingerprint images from individuals. The related work/literature is presented in section 4.2. Section 4.3 describes the proposed multiple enrollment algorithms using spectral minutiae. An explanation of the fingerprint databases and other methods used, the setup of the research experiments, and the implementation environment used is provided, the results presented, evaluations and discussions made and finally a conclusion drawn.

4.1 Introduction

The demand for higher security and more convenient operations for the case of access control and personal data protection spur intensive research, deployment and commercialization of biometric systems. Distinct from traditional identification methods, which rely on what you know (for example PIN, Password) or what you have (like key, token), a biometric system makes judgments based on what you are, and thus meets more stringent security requirements, while relieving users from the burden of remembering passwords [10]. Using fingerprints as a biometric characteristic is one of the oldest and widely used method for recognition [10]. Acquiring accurate fingerprint images for recognition in a one-time capture is infeasible; because not all the necessary and distinguishable fingerprint information may be collected. Enrollment using multiple fingerprint samples (multiple enrollment) is a solution that can help in extending the information of a single enrolled fingerprint image, assure the reliability of each fingerprint image and also improve the recognition accuracy of a fingerprint recognition system by lowering the error rates, allowing robustness by lowering the False Rejection Rates for low quality or worn-out fingerprint images and also make spoofing harder. However, the variability and typicality of an individual's multiple acquired fingerprints can be of concern in a fingerprint recognition system. For instance, when the with-in variance of the multiple enrolled fingerprints is too small or too large to represent the actual fingerprint variability of a given individual. This variability can be as a result of noise, errors in the feature extraction module, fingerprint displacement and rotation during the enrollment or capture stage, distortion, etc. It is also possible that the different multiple acquired fingerprints of the same finger could certainly portray different parts of the finger's surface, hence causing the variability.

This Chapter provides an evaluation of the effectiveness of using multiple enrollment in fingerprint recognition systems. Multiple enrollment experiments were carried out and the recognition performance improvements resulting from the deployment of multiple enrollment using a Traditional minutiae based matching method and a Spectral Minutiae-based matching method were investigated.

4.2 Related Work

Biometric fusion with respect to fingerprints has been in use for quite a long time; mainly in the law enforcement field [10]. Due to its impact on the recognition performance of biometric systems, fusion has increasingly attracted a vast amount of research. To realize this impact, different researchers have explored the fusion approach by taking up any of the forms and implementation levels. Fusion can be carried out based on the information source chosen. First, using multiple traits as the source of information. For instance, fingerprint and face where a user would be required to swipe his finger first and then verify by presenting his face, fingerprint and voice[49] where the user swipes his finger and has to also answer some questions based on the provided challenges (see [102] for more details about a challenge-response-based voice recognition system), fingerprint and iris, fingerprint and hand geometry [42], face and speech [103, 104, 105] etc. When fingerprints are fused with other biometric traits, it is not only a higher recognition accuracy that is achieved but the system also becomes more robust to imposter attacks and also more difficult to fool. It is also possible that a number of users may not possess a particular biometric which qualifies multiple traits biometric a good option. An example of fusion research performed using a number of multiple traits is one in [40] where three biometric traits; face, fingerprint and hand geometry were combined. With such a system, a high recognition performance is achieved and it is difficult for an intruder to spoof the multiple traits simultaneously. The most common levels of fusion that have been used in the multiple traits based recognition systems are score or rank levels; this is due to the differences in representations among the traits [10]. Another source of information that has often been used for fingerprint fusion is multiple fingers of the same person, where two or more fingers of the same person are combined. For this kind of fusion, it is required to choose which fingers to be used from both hands and also in what order the users would present them at enrollment and verification. For example in the FVC2000 [15], up to four fingers were collected from each person; taking the forefinger and middle finger of both hands. Similar to fusion using multiple traits, it is not only a higher recognition accuracy that can be achieved but the fingerprint recognition system also becomes more difficult to fool. Fusion at score-level has been the most popularly used implementation level for multi-finger recognition systems; although it is also possible to fuse multiple fingers at other levels.

4.2.1 Recognition Performance improvement with Multi-Sample Fusion

Studies from different researchers [37, 40, 41, 33, 106, 35] show that a better recognition performance is attained when fusion of multiple sources of information is used than when a single source is used. Hybrid biometric systems like one in[47] which use the face and fingerprint as primary traits together with gender, ethnicity, and height as the soft characteristics also shows a significant recognition performance improvement. In their research “decision-level fusion in fingerprint recognition" [44], Prabhakar and Jain show that if different fingerprint matching algorithms are combined (four algorithms were used), the overall performance is increased. Not only that, but they also show that combining multiple impressions or multiple fingers improves the verification performance of the fingerprint recognition system.

4.3 Spectral Minutiae-based Multiple Enrollment Fingerprint Recognition

In this method, all the minutiae templates are first extracted using Verifinger 6.0.0.7 extractor and later stored with unique names. The extracted fingerprint minutiae sets are then transformed into a spectral minutiae form (called Minutiae Spectrum) by representing them as a fixed-length feature vector which is invariant to translation. In the Minutiae Spectrum form, rotation and scaling also become translations which can easily be compensated for. Once the transformation into a Spectral Minutiae representation is done, direct matching follows by correlation between the two Spectral images and a similarity score is generated. In the Figure 2 is the fingerprint image sample while Figure 3, is its Spectral Minutiae representation (Minutiae spectrum) from the SAS-DB2 database. The horizontal axis of the Minutiae spectrum represents the rotation angle of the spectral magnitude while the vertical axis represents the frequency of the spectral magnitude. Readers interesting in more information regarding this method are referred to [98].

Figure 2: Fingerprint Image Sample (Extracted from SAS-DB2)

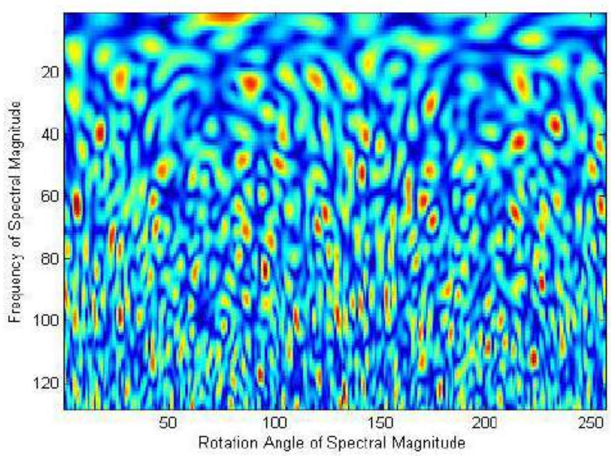

Figure 3: Minutiae Spectrum

4.3.1 The Spectral Minutiae Multiple Enrollment Algorithm

A Spectral Minutiae Multiple Enrolment algorithm was designed and used to perform genuine and impostor comparisons as described below.

A. Spectral Minutiae-based Multiple Enrollment Algorithm for Genuine Comparisons

For multiple genuine pair matching in FVC2000-DB2 database, four fingerprints of the same person, each as a reference are chosen matching each of them with the fifth sample of that person as the test fingerprint. For multiple genuine pair matching in SAS-DB2 database, six fingerprints of the same person, each as a reference are chosen matching each of them with the seventh sample of that person as the test fingerprint. The algorithm follows the following steps;

1. *Find the minutiae template storage location (database) for all IDs*
2. *Choose an ID for which multi-sample enrollment and single sample verification is to be done*
3. *Choose the 4 (in case of FVC2000-DB2 database) or 6 (in case of SAS-DB2 database) minutiae templates of that ID for multi-sample enrollment*
4. *Search database for their existence*
5. *If template exists, load it, transform it to a Spectral minutiae template, uniquely name it and store it*
6. *Select one of the other 4 (in case of FVC2000-DB2 database) or 6 (in case of SAS-DB2 database) minutiae templates (samples) of that ID for single sample verification*
7. *Steps 4 and 5 are repeated*
8. *Direct Spectral Minutiae matching between the two stored spectral minutiae templates follows and a genuine matching score generated.*
9. *Store the Genuine score in a matrix*
10. *Select another minutiae template (sample) of that ID for single-sample verification*
11. *Repeat steps 7 to 9*
12. *Repeat steps 10 and 11 for all other samples (Spectral minutiae templates) of that ID for single-sample verification*
13. *Choose the maximum score amongst the 4 scores (in case of FVC2000-DB2 database) or the 6 scores (in case of SAS-DB2 database) and store it in a matrix*
14. *Choose another ID for which multi-sample enrollment and single sample verification is to be done*
15. *Repeat steps 3 through 14 until the last ID in database*

B. Spectral Minutiae-based Multiple Enrollment Algorithm for Impostor Comparisons

For multiple impostor pair matching in FVC2000-DB2 database, we chose the first sample of an identity (ID) in the database and matched it with four multiple enrollment samples of the different identities (IDs). While for multiple impostor pair matching in SAS-DB2 database, we chose the first sample of an identity (ID) in the database and matched it with the six multiple enrollment samples of the different identities (IDs). The algorithm follows the following steps:

1. *Find the minutiae template storage location (database) for all IDs*
2. *Choose an ID (ID1) to use for enrollment*
3. *Choose a different ID (ID2) for impostor matching*
4. *Select the first minutiae template (sample) of ID1 for enrollment*
5. *Search database for its existence*
6. *If template exists, load it, transform it to a Spectral minutiae template, uniquely name it and store it*
7. *Select one of the 4 (in case of FVC2000-DB2 database) or 6 (in case of SASDB2 database) minutiae templates (samples) of ID2 that were used in multi sample enrollment, for impostor verification*
8. *Steps 5 and 6 are repeated*
9. *Direct Spectral Minutiae matching between the two stored spectral minutiae templates follows and an Impostor matching score generated.*
10. *Store the Impostor score in a matrix*
11. *Select another Spectral minutiae template (sample) of ID2 for verification*
12. *Repeat steps 8 to 10*
13. *Repeat steps 11 and 12 for all other samples (Spectral minutiae templates) of ID2 for verification*
14. *Choose the maximum score amongst the 4 scores (in case of FVC2000-DB2 database) or the 6 scores (in case of SAS-DB2 database) and store it in a matrix*
15. *Choose another different ID (ID2) for impostor matching*
16. *Repeat steps 7 to 15 until last ID2 in database (excluding Current ID1)*
17. *Choose another ID (ID1) to use for enrollment*
18. *Repeat steps 4 through 17 for all IDs*

4.4 Implementation Environment, Fingerprint Database Used, Matching methods used and Experimental Setup

A description of the implementation environment, the fingerprint databases used, the matching methods used and the setup of all experiments is provided for in Chapter three.

4.5 Results, Evaluations and Discussions

This section presents the results, evaluations and discussions.

4.5.1 Results

4.5.1.1 Experiments on the FVC2000-DB2 Fingerprint Database

A. Using Traditional Minutiae-based Matching

In this experiment, the VeriFinger 6.0.0.7 matcher was used for fingerprint matching to attain the similarity scores. The fingerprint samples from ID 1 to 100 were used for testing, each contributing all the 8 samples. In the single sample enrollment test case, all the possible combinations for the genuine comparisons were used and for imposter comparisons; the first sample of each ID in the database was used. Therefore, 100 x ((8 x 7)/2) = 2800 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons were generated with an EER of 0.75%. Four permutation sets, Set1, Set2, Set3 and Set4 for multi-sample enrollment and single-sample genuine verification were established. For impostor verification, the first sample of an identity in the database was chosen and compared with the four multiple enrollment samples of the different IDs. For each permutation set, a multi-sample enrollment and single-sample verification was done to realize the recognition performances amongst the sets. In each set 400 genuine comparisons and 9900 impostor comparisons we generated. The following EERs: 0.25%, 0.00%, 0.25% and 0.00% were attained, respectively for Set1, Set2, Set3 and Set4. The whole multiple enrollment experiment generated 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons with an EER of 0.13%.

B. Using Spectral Minutiae-based Matching

In this experiment, the similarity scores were generated by direct spectral minutiae matching. All the possible combinations for the genuine comparisons in the single-sample enrollment test case were used and for imposter comparisons; the first sample of each ID in the database was used. In total, 100 x ((8 x 7)/2) = 2800 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons were generated and an EER of 6.14% was attained. For the multi-sample enrollment test case, four permutation sets, Set1, Set2, Set3 and Set4 were established for multi-sample enrollment and single-sample genuine verification. For impostor verification, the first sample of an identity in the database was chosen and compared with the four multiple enrollment samples of the different IDs. For each permutation set, a multi-sample enrollment and single-sample verification was also performed to check the recognition performance improvements amongst the sets. In each set 400 genuine comparisons and 9900 impostor comparisons were generated and the following EERs were attained: 2.00%, 2.25%, 1.25% and 2.00%, respectively for Set1, Set2, Set3 and Set4. The whole multiple enrollment experiment generated 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons with an EER of 1.75%. Table 5 provides a summary of the experimentation results mentioned above.

4.5.1.2 Experiments on the SAS-DB2 Fingerprint Database

A. Using Traditional Minutiae-based Matching

In this experiment, the VeriFinger 6.0.0.7 matcher was used for fingerprint matching to attain the similarity scores. The fingerprint samples from ID 1 to 100 were used for testing, each contributing all the 12 samples. For the single-sample enrollment test case, all the possible combinations for the genuine comparisons were used. And for imposter comparisons, the first sample of each ID in the database was used. This in total resulted in 100 x ((12 x 11)/2) = 6600 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons. An EER of 1.14% was achieved. Six permutation sets, Set1, Set2, Set3, Set4, Set5 and Set6 were established for multi-sample enrollment and single-sample genuine verification. For impostor verification, the first sample of an identity in the database was chosen and compared it with the six multiple enrollment samples of the different IDs. For each permutation set, a multi-sample enrollment and single-sample verification was performed to observe the recognition performance improvements amongst the sets. For each set 600 genuine comparisons and 9900 impostor comparisons were generated and the following EERs: 1.00%, 0.00%, 0.33%, 0.00%, 0.00% and 0.33%, were respectively obtained for Set1, Set2, Set3, Set4, Set5 and Set6. The whole multiple enrollment experiment generated 100 x 6 x 6 = 3600 genuine comparisons and 100 x 99 x 6 = 59400 impostor comparisons with an EER of 0.28%.

B. Using Spectral Minutiae-based Matching

In this experiment, the similarity scores were attained by direct spectral minutiae matching. For single-sample enrollment, all the possible combinations for the genuine comparisons were used and the first sample of each ID in the database was used for the imposter comparisons. In total, 100 x ((12 x 11)/2) = 6600 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons were generated. An EER of 14.97% of was attained. For the multi-sample enrollment test case, six permutation sets, Set1, Set2, Set3, Set4, Set5 and Set6 were formulated for multi-sample enrollment and single sample genuine verification. For impostor verification, the first sample of an identity in the database was chosen and compared with the six multiple enrollment samples of the different IDs. For each permutation set, multi-sample enrollment and single-sample verification was performed to check the recognition performance improvements amongst the sets. In each set 600 genuine comparisons and 9900 impostor comparisons were generated and the following EERs were attained: 9.67%, 5.67%, 7.00%, 6.50%, 5.67% and 6.50%, respectively for Set1, Set2, Set3, Set4, Set5 and Set6. The whole multiple enrollment experiment generated 100 x 6 x 6 = 3600 genuine comparisons and 100 x 99 x 6 = 59400 impostor comparisons and an EER of 6.94%. Table 6 provides a summary of the experimentation results mentioned above.

Table 5: Summary of FVC2000-DB2 Experimentation Results

Matching Method	Single Enrollment	Multiple Enrollment				
		Set1	Set2	Set3	Set4	Overall
Traditional Minutiae Based	0.75%	0.25%	0.00%	0.25%	0.00%	0.13%
Spectral Minutiae Based	6.14%	2.00%	2.25%	1.25%	2.00%	1.75%

Matching Method	Single Enrollment	Multiple Enrollment						
		Set1	Set2	Set3	Set4	Set5	Set6	Overall
Traditional Minutiae Based	1.14%	1.00%	0.00%	0.33%	0.00%	0.00%	0.33%	0.28%
Spectral Minutiae Based	14.97%	9.67%	5.67%	7.00%	6.50%	5.67%	6.50%	6.94%

Table 6: Summary of SAS-DB2 Experimentation Results

4.5.2 Evaluations

4.5.2.1 FVC2000-DB2 Database

A. Using Traditional Minutiae-based Matching

The results show that multiple enrollment per set outperformed single enrollment. Single enrollment with this method achieved an EER of 0.75% while the EERs for individual set multiple enrollment were: 0.25%, 0.00%, 0.25% and 0.00% respectively for Set1, Set2, Set3 and Set4. Similarly, the overall multiple enrollment recognition performance of EER 0.13% outperformed the single enrollment performance of EER 0.75%.

B. Using Spectral Minutiae-based Matching

Here, multiple enrollment per set using this matching method also outperformed single enrollment. For this method, single enrollment attained an EER of 6.14% while EERs of: 2.00%, 2.25%, 1.25% and 2.00% were respectively achieved for Set1, Set2, Set3 and Set4 using multiple enrollment. The overall multiple enrollment recognition performance of EER 1.75% also outperformed the single enrollment one of EER 6.14%.

4.5.2.2 SAS-DB2 Database

A. Using Traditional Minutiae-based Matching

The recognition performance attained in each set outperformed the one in single enrollment. EERs of 1.00%, 0.00%, 0.33%, 0.00%, 0.00% and 0.33%, were respectively achieved for Set1, Set2, Set3, Set4, Set5 and Set6 using multiple enrollment, compared to the 1.14% EER attained from single enrollment. The overall, multiple enrollment recognition performance of EER 0.28% also outperformed the EER of 1.14% resulting from the single enrollment experiment.

B. Using Spectral Minutiae-based Matching

Under this experiment, multiple enrollment per set also outperformed the single enrollment performance. For the individual sets, the EERs attained using multiple enrollment were: 9.67%, 5.67%, 7.00%, 6.50%, 5.67% and 6.50%, respectively for Set1, Set2, Set3, Set4, Set5 and Set6 compared to the 14.97% EER resulting from single enrollment. On the other hand, the overall multiple enrollment recognition performance of 6.94% also outperformed the single enrollment performance of ERR 14.97%.

4.5.2.3 Performance Improvement

An objective evaluation of multiple enrollment by considering the performance improvement in matching accuracy using both matching methods was performed. Multiple enrollment using the first method resulted in an 83.33% improvement in recognition rate over a set of 800 fingerprint images in FVC2000-DB2 database and a 75.55% improvement in recognition rate over a set of 1200 fingerprint images in SASDB2 database. On the other hand, multiple enrollment using the second method results in a 71.51% improvement in recognition rate over a set of 800 fingerprint images in FVC2000-DB2 database and a 53.61% improvement in recognition rate over a set of 1200 fingerprint images in SAS-DB2 database. Table 7 provides a summary of the experimentation results together with the performance improvements achieved.

Table 7: Experimentation Results and Performance Improvement.

Matching Method	**Fingerprint Database**	**Single Enrollment**	**Multiple Enrollment**	**Performance Improvement**
Traditional Minutiae Based	FVC2000-DB2	0.75%	0.13%	83.33%
	SAS-DB2	1.14%	0.28%	75.55%
Spectral Minutiae Based	FVC2000-DB2	6.14%	1.75%	71.51%
	SAS-DB2	14.97%	6.94%	53.61%

4.5.2.4 Comparison of Results

Comparing with other researchers [62, 60, 61, 107, 56, 48, 36, 43, 52] who have carried out multi-sample/model fusion (with some having multiple enrollment) using minutiae as the desirable identification feature; the results presented above outperform theirs in terms of Equal Error Rates (EER). This clearly shows that the algorithms are more superior by over 38.1% to the ones presented in [62, 60, 61, 88, 56, 48, 35, 43, 52]. However, there was no consideration in recording the processing time for feeding so many fingerprints and acquiring results; this was left for future work.

4.5.3 Discussions

The experimentation results and evaluations presented show that multiple enrollment as whole out performs single enrollment and the overall performance improved by more than a 50% recognition rate. For a typical biometric security system, an improvement in recognition rate of more than 50% is a great achievement. This performance improvement can be attributed to the fact that, the source of information becomes large making it is easy to compensate for outliers such as rotations, noise, displacements, etc. It is also true that the lesser the outliers, the better the recognition performance.

Despite the great improvement in recognition rate, multiple enrollment still comes with challenges. One is the high storage demand and a slow matching/comparison speed. The comparison and computation time are really too high for a seamless real-time fingerprint recognition system. The minutiae-based methods themselves have a relatively slow comparison speed; although their recognition performance is very good most especially for good quality fingerprints. Minutiae templates are big in size and therefore affect comparison time as well as storage on smaller devices would be challenging. Future work should aim at other methods/algorithms to check both performance improvement and comparison speed while using multiple enrollment for real-time fingerprint recognition systems. Also, not all the input fingerprint samples corresponding to an individual were of good quality. Extraction of desirable features from the low quality fingerprint samples can also greatly affect the recognition performance. A good multi-sample fusion scheme to help in such a situation would be one that could automatically allocate lower weight values to low quality fingerprint samples and higher weight values to good quality fingerprint samples and then later choose ones with higher weight values for fusion. User cooperation and training would also be crucial for a typical security biometric system. All the experiments in this research were performed on data from un-trained persons. Performance from multiple enrollment can even be better when the users are trained.

4.6 Conclusions

This chapter introduced the basic concept of multiple enrollment for fingerprint recognition to determine its viability and effectiveness in fingerprint recognition systems. A multiple enrollment algorithm was designed and used together with existing fingerprint recognition techniques to carry out an evaluation. An evaluation of multiple enrollment was done in comparison to single enrollment using two methods, first, a Traditional minutiae based matching method and second, a Spectral Minutiae-based matching method. The evaluation was carried out on two fingerprint databases; SAS-DB2 and FVC2000-DB2 databases. The experimentation results and evaluations show that multiple enrollment as whole greatly outperforms single enrollment in terms of recognition performance.

The contribution of this chapter is a new multiple enrollment algorithm with a better recognition performance using a new fingerprint representation (minutiae spectrum).

CHAPTER FIVE: RECOGNITION PERFORMANCE IMPROVEMENT

This chapter provides a novel approach that performs prior selection of good fingerprint image samples of an individual for matching to further improve recognition performance, reduce the matching speed as well as memory consumption. Section 5.1 of this chapter introduces the challenges faced during fingerprint image capture, Section 5.2 presents the related work/literature, while Section 5.3 provides an overview of the designed multiple enrollment approach. The designed multiple enrollment approach first selects only the good quality fingerprint images amongst the many multiple enrolled images per individual for matching. The approach also uses a threshold to further eliminate bad results for a better performance accuracy improvement, matching speed and memory consumption reduction. An explanation of how the experiments were setup and the environment in which they were implemented, the fingerprint databases and other methods used is provided in Chapter three Section 3. The results are presented, discussed and conclusions made from Section 5.5 through 5.6 respectively.

5.1 Introduction/Background

In fingerprint recognition systems, it is almost infeasible to capture good quality (accurate) fingerprint images for recognition at one time. This is because, not all the required distinct fingerprint features may be collected. This can be attributed to a number of factors such as noise, errors in the feature extraction module, fingerprint displacement and rotation during the enrollment or capture stage, distortion, low quality fingerprint images, worn-out fingerprint images, partial overlap, finger pressure and skin conditions [10], [15]. The factors mentioned above negatively affect the recognition performance/accuracy and make it hard to relay on single enrollment where one fingerprint sample is collected per individual at one time.

A number of researchers have for long proposed that enrollment of individuals using multiple fingerprint samples (multiple enrollment) would be a solution that could help in extending the information of a single enrolled fingerprint image and also ensure the reliability of each fingerprint image [10]. Multiple enrollment can also improve the recognition accuracy of the fingerprint recognition system by lowering the error rates, allowing robustness by lowering the False Rejection Rates for low quality or worn-out fingerprint images and also make spoofing harder [10].

From our previous research [17], [108], [109] and others (see related work), it is indeed true that multiple enrollment supports improvement in recognition accuracy of fingerprint recognition systems. It was however noted that there is still a challenge in designing and developing usable, acceptable, implementable and robust [18] multiple enrollment based fingerprint recognition systems (algorithms) that can match only high quality fingerprints amongst the many enrolled fingerprint samples, with a high matching speed, little memory consumption but still maintaining a high recognition accuracy. These challenges make it almost impossible to implement multiple enrollment based fingerprint recognition systems in real-world applications.

This chapter presents a novel approach towards design of multiple enrollment based fingerprint recognition systems which greatly improves the recognition accuracy, taking into account the running time/speed as well as memory consumption; by first selecting only the good quality fingerprint images amongst the many multiple enrolled images per individual for matching.

5.2 Related work

A lot of research that has been done relating to multiple enrollment has mainly focused on combining multiple fingerprint matchers (algorithms), like in [78], [43], [51], [60], [79], [44], and in some cases combining multiple fingerprint sensors, like in [48] to achieve better recognition accuracy; rather than concentrating on single fingerprint matchers focusing on multiple enrollment of fingerprints. Others like [56], [37], [34], [47], [35], [33], [40], and [41], have focused on fusion of multiple sources of information to improve recognition performance. From the analysis of the previously done research related to multiple enrollment, some of the researchers have implemented decision level fusion in fingerprint verification; whereas the majority have implemented score level fusion and others have tried to combine the two in some cases. From the literature searched, it is also evident that there is a lot of interest in combining multiple sources of biometric information to improve the recognition accuracy.

However, on top of the avenues for improving recognition accuracy, little research has concentrated on improving the matching speed of such multiple source based biometric systems, usability, memory consumption and acceptability. Although multi-modal, multi-sensor, multi-matcher/algorithm based fingerprint recognition systems improve the recognition performance, their implementation, usability, memory consumption and acceptability in real-world deployment situations may not easily be achieved; it would require more costs to acquire the necessary extra resources, implement as well as convincing and training users to adapt to them. The analyzed recognition accuracies arising from the surveyed previously done research are also still low. This was the driving force for us to embark on this research; to find better ways of designing multiple enrollment based fingerprint recognition systems.

5.3 The Recognition Performance Improvement Multiple Enrollment Approach

A novel multiple enrollment fingerprint recognition approach that further improves recognition accuracy, the matching speed and reduces memory consumption in multiple enrollment based fingerprint recognition systems was designed.

This approach focuses on selection prior to matching by determining good images and eliminating the bad images amongst all the multiple enrolled images of each individual. To differentiate good images from bad images amongst all the multiple enrolled samples of an individual, the amount of minutiae features extracted for each stored template are counted. Naser Zaeri in his book chapter minutiae-based Fingerprint Extraction and Recognition [146] reports that a good fingerprint image contains typically about 40 – 100 minutiae, while in latent or partial fingerprints, the number of minutiae is much less (approximately 20 to 30 minutiae). It is therefore reasonable from this background that we consider to choose images that contain a good number of minutiae starting from the range above the poor images on words. In our approach, if a template amongst the many templates possesses a high number of minutiae features extracted, it is chosen as a good image for matching else it is discarded and considered a bad image sample. This is so because, the more the number of minutiae features extracted from an image, the more likely that image sample will be from the same individual since direct matching by correlation between the two images will have based on enough features for comparison. In this case a better similarity score is generated rather than when a bad image (possessing fewer extracted features) is matched with a good image. This also implies that most of the image features would have been extracted and that the image is clear and of good quality. Kulshrestha et al [147] also argue that the final recognition performance of a fingerprint authentication system directly relates to the quality of the fingerprint images. Their argument follows that “good images need only minor processing and enhancement for accurate future detection algorithms”

This therefore implies that after the selection has been done, it is only the good fingerprint image samples that are chosen during the matching (fusion) process to improve the recognition accuracy, matching speed as well as reduce on the memory consumption (This explains Algorithm two-*Alg2* functionality whose outputs are presented in the results section).

In this approach, a threshold was set to eliminate any further low results that algorithm two could have generated hence more improvement in recognition accuracy, matching speed as well as reduction in memory consumption (This explains Algorithm three-*Alg3* whose outputs are also presented in the results section)

Algorithm one (*Alg1*) is the original algorithm as discussed in our previous work [17], [108] and performs no unique cleverness but simply matches all the multiple enrolled fingerprint image samples of each individual as stored in the database. It is important to note that *Alg2* and *Alg3* are subsequent modifications of *Alg1* and *Alg2* respectively.

5.3.1 Multiple Genuine Comparisons

The three algorithms (*Alg1, Alg2,* and *Alg3*) as discussed in section 5.3 were designed for genuine comparisons to realize a better contrast in recognition performance as well as running time/speed improvement and reduction in memory consumption in multiple enrollment based fingerprint recognition systems.

5.3.2 Multiple Impostor Comparisons

Impostor comparisons usually generate very low results since comparisons (matching) is done based on one individual's fingerprint image samples with other individuals'(as impostors) image samples in the whole database. Also, three algorithms (*Alg1*, *Alg2* and *Alg3*) were designed for impostor comparisons; where *Alg2* chooses the bad image samples amongst the many enrolled samples for each other individuals' (impostors') samples, *Alg3* uses a threshold to eliminate any high results that *Alg2* could have generated and *Alg1* (the original) performs no unique cleverness during impostor matching. Although impostor matching normally generates low results, this approach presented continues to select bad images prior to matching to consider lower results and make allowance for a more stringent security check.

5.4 Implementation Environment, Fingerprint Database Used, Matching methods used and Experimental Setup

A description of the implementation environment, the fingerprint databases used, the matching methods used and the setup of all experiments is provided for in Chapter three.

5.5 Results and Discussions

This section presents the results, their discussions and the future work.

5.5.1 Results

5.5.1.1 Experiments on the FVC2000-DB2 Fingerprint Database

For all the three algorithms, four permutation sets, Set1, Set2, Set3 and Set4 were established for multi-sample enrollment and single-sample genuine verification. For impostor verification, the first sample of an identity in the database was chosen and compared with the four multiple enrollment samples of the different IDs.

In algorithm one-*Alg1* (original), for each permutation set, multi-sample enrollment and single-sample verification was carried out to check the recognition performance improvements amongst the sets. In each set 400 genuine comparisons and 9900 impostor comparisons were generated.

For the whole multiple enrollment experiment using *Alg1*, 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons were generated. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set are shown in Table 8.

5.5.1.2 Experiments on the FVC2006-DB2 Fingerprint Database

For all the three algorithms, six permutation sets, *Set1*, *Set2*, *Set3*, *Set4*, *Set5* and *Set6* were established for multi-sample enrollment and single-sample genuine verification. For impostor verification, the first sample of an identity in the database was chosen and compared with the six multiple enrollment samples of the different IDs.

In algorithm one-*Alg1* (original), for each permutation set, multi-sample enrollment and single-sample verification was performed to check the recognition performance improvements amongst the sets. In each set 840 genuine comparisons and 19460 impostor comparisons were generated.

For the whole multiple enrollment experiment, 140 x 6 x 6 = 5040 genuine comparisons and 140 x 139 x 6 = 116760 impostor comparisons were generated. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set are shown in Table 9.

5.5.1.3 Remarks

It is important to note that for both databases, the genuine comparisons for algorithm one (*Alg1*) were fixed because the algorithm does not perform any kind of special image selections prior to matching. For algorithm two (*Alg2*), the total genuine comparisons differ because they were generated based on the selected good quality images for matching by the algorithm. The genuine comparisons for algorithm three (*Alg3*) also differ because they were generated based on a threshold that was set to eliminate any further low results that algorithm two (*Alg2*) could have generated.

Table 8 provides the experimentation results on FVC2000 DB2-A databases while Table 9 provides the experimentation results on FVC2006 DB2-A database.

Table 8: Summary of Experimentation Results on FVC2000 DB2-A Database

FVC 2000-DB2	Recognition Performance			Running Time /Speed (sec)			Peak Memory Consumption(KB)		
Permutation Set	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**
Set1	2.00%	1.12%	0.00%	337.01	207.82	167.42	960	148	16
Set2	2.25%	0.75%	0.00%	235.38	173.75	169.59	320	148	64
Set3	1.25%	1.09%	0.00%	231.75	169.10	166.51	148	92	16
Set4	2.00%	1.85%	0.00%	232.82	170.57	168.79	148	44	16

Table 9: Summary of Experimentation Results on FVC2006 DB2-A Database

FVC 2006-DB2	Recognition Performance			Running Time/Speed (sec)			Peak Memory Consumption(KB)		
Permutation Set	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**
Set1	0.95%	0.75%	0.00%	594.58	582.42	561.58	364	256	44
Set2	1.19%	0.76%	0.00%	593.40	581.42	562.91	324	192	108
Set3	1.07%	0.63%	0.00%	723.78	700.93	675.65	320	260	128
Set4	0.95%	0.51%	0.00%	704.87	588.83	578.27	320	192	148
Set5	1.19%	0.76%	0.00%	622.81	547.42	528.84	448	256	192
Set6	1.19%	1.02%	0.00%	547.95	539.18	536.16	320	260	192

5.5.2 Discussions

The results presented in Table 8 and Table 9 demonstrate a significant improvement in recognition performance, running time and memory consumption. Comparing algorithm one (*Alg1*) which was our previously presented algorithm in [17, 108], with algorithm two (*Alg2*) and three (*Alg3*) which are subsequent improvements of *Alg1*, it can be observed that the recognition performance, for all the permutation sets greatly improved, whereas the matching speed and peak memory consumption drastically reduced when *Alg2* and *Alg3* were applied respectively (This can be seen from the left hand side of the Tables 8 and 9 to the right hand side). The reason for this significant improvement can be attributed to the fact that, *Alg1* in its state performs matching of all the multiple enrolled samples of the individual whether good or bad which increases the matching speed as well as the memory consumption. The more the images to match the more time it takes and the more memory it consumes. On the other hand, *Alg2* performs prior selection of only the good images of the multiple enrolled samples of the individual before matching. After selection, then matching continues for only the chosen good samples. With this, the matching speed and memory consumption greatly reduce since there are now fewer samples for matching per individual. This also applies to *Alg3*; which on top of prior selection to matching uses a threshold to eliminate any further low results that *Alg2* could have generated. Because of this further elimination, the recognition performance is to its best and the matching speed as well as the memory consumption also further reduce.

A comparative assessment of the attained results with the existing ones presented in literature (Section 2.5.1) shows that they are more superior by over 29.6% with algorithm two (Alg2) and by 100% with algorithm three (*Alg3*) and can be recommendable for future deployment in real world multiple enrollment based fingerprint recognition applications.

5.6 Conclusions

This Chapter first introduces the challenges faced during fingerprint image capture and the fact that the current multiple enrollment based fingerprint recognition systems still suffer poor matching speeds, a lot of memory consumption and the recognition accuracies are still very low hence making implementation in real-world applications difficult. A novel approach that performed prior selection of good fingerprint image samples of an individual for matching to further improve recognition performance, reduce the matching speed as well as memory consumption was designed. A spectral minutiae based matching method and two fingerprint databases (FVC2000-DB2 and FVC2006-DB2) were used. A comparison of the attained results with the existing ones presented in literature shows that they are more superior. This therefore makes it possible to design better multiple enrollment based fingerprint recognition systems with a high recognition accuracy, high matching speed and low memory consumption using the approach presented in this chapter.

With respect to research question two of this thesis that was formulated in Section 1.4, this chapter addresses objective number two, three and four by providing a novel approach to multiple enrollment based fingerprint recognition systems design. A multiple enrollment based fingerprint recognition system was designed, implemented (simulated) and tested to check recognition performance, speed as well as memory consumption.

The contribution of this chapter is a novel approach that performs prior selection of good fingerprint image samples of an individual for matching to further improve recognition performance, reduce the matching speed as well as memory consumption.

CHAPTER SIX: GABOR FILTER BASED FINGERPRINT RECOGNITION

This chapter presents a non-minutiae fingerprint matching technique; Gabor filter-based approach, the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. Section 6.1 of this chapter introduces the challenges faced by minutiae based matching approaches, Section 6.2 presents the related work/literature while Section 6.3 provides an overview of the designed Gabor-filter based multiple enrollment matching approach. The designed approach first extracts Gabor features from all input fingerprint image sample, creates column vectors of the extracted features, normalizes them to zero mean and unit variance and finally stores them with unique identifications (IDS). Direct matching then follows calculating the Euclidean distance between the two feature vectors originating from the two fingerprint samples to be compared. It is from this Euclidean distance value obtained that a matching score is computed and standardized. An explanation of how the experiments were setup and the environment in which they were implemented, the fingerprint databases and other methods used is provided in chapter three. In Section 6.5 through 6.6, the results are presented, their discussion and comparisons made and conclusions drawn respectively.

6.1 Introduction

The notion of multiple enrollment in fingerprint recognition systems has been an interesting research area for long; where researchers have proposed the use of multiple fingerprint samples to extend information of single enrolled fingerprint images, to ensure reliability of the fingerprint images and also to improve the recognition performance/accuracy of fingerprint recognition systems [10]. Researchers such as [62], [45], [60], [26], [27] and others in the related work section have mostly concentrated on minutiae-based matching methods while setting up multiple enrollment based fingerprint recognition systems. Other than minutiae-based matching methods, correlation based methods like [110], [111], [112], [113], [114] and pattern based methods such as [22], [94], [95] have been used for verification, indexing and identification in fingerprint recognition; but have rarely been implemented in multiple enrollment based fingerprint recognition systems. Jain et al [69] point out that minutiae-based approaches suffer the difficulty of automatically extracting all minutiae points due to failure to detect the complete ridge structures of a fingerprint. Based on the above scenario, matching becomes a difficult process for the case of two fingerprints having different numbers of uncaptured minutiae points. Furthermore, it is also difficult to describe all the local ridge structures as minutiae points, hence making matching a difficult process. A general overview of the minutiae-based methods is that, with poor quality fingerprint images, detection of minutiae points would be difficult hence affecting their resulting performance. Non-minutiae based techniques such as Gabor filtering are rich in terms of distinguishing features and can be used as an alternative since they capture both the local and global details in a fingerprint.

This chapter presents a Gabor filter-based approach; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system.

6.2 Related Work

Multiple enrollment for fingerprint recognition is an old study area that has received a vast amount of research [109]. Minutiae based techniques such as [115], [116], [117] [118], [119] and [109] have been widely used in designing multiple enrollment fingerprint recognition systems. Although minutiae-based techniques have been widely used [120], they suffer the difficulty of automatically extracting all minutiae points due to failure to detect the complete ridge structures of a fingerprint. It is also difficult to quickly match two fingerprints that have a difference in the number of unregistered minutiae. Furthermore, it is also difficult to describe all the local ridge structures as minutiae points, hence making matching a difficult process [69]. Minutiae extraction also takes a lot of time [76]. Gabor filter-based techniques such as [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], have also attracted a lot of interest in designing fingerprint recognition systems. Gabor based fingerprint matching techniques are known to be rich in terms of distinguishing features and can be used as an alternative since they capture both the local and global details in a fingerprint. Their resultant representation is scale, translation and rotation invariant. They also produce short fixed length feature vectors, which makes them appropriate for indexing, faster fingerprint matching and storage on smaller devices[76]. On analysis of the literature, it was observed that the current research in using Gabor filter-based techniques has mainly focused on single enrollment rather than multiple enrollment for fingerprint recognition. It was also noted that there has been little or no focus on the running time/speed as well as memory consumption while using Gabor filter-based techniques. These gaps were a critical motivating factor in carrying out this research; to determine the possibility and viability of implementing Gabor filter-based techniques in the design of multiple enrollment based fingerprint recognition systems.

6.3 Gabor Filter-Based Multiple Enrollment Fingerprint Recognition

In this method, the Gabor features of all input fingerprint image samples are first extracted like in [99]. Column vectors consisting of the Gabor features of the input fingerprint image samples are created. These feature vectors are normalized to zero mean and unit variance (to remove any noise originating from sensors as well as the grey level background which maybe generated because of the finger pressure differences), and then stored with unique identification (ID) names. Direct matching follows by calculating the Euclidean distance (see Equation 1-*Eq*1) between the two feature vectors; *Fvec1* and *Fvec2* respectively originating from the two fingerprint samples to be compared. Based on this Euclidean distance(*Ed*) value attained, a matching score is computed such that; the higher the Euclidean distance(*Ed)*, the lower the matching score and vice versa. The score is computed and standardized as shown in Equation 2 (*Eq*2) [100]. Figure 4 shows a fingerprint image, Figure 5 shows the real parts of the Gabor filters while Figure 6 its respective magnitudes of the Gabor filters

Euclidean Distance(*Ed*) = $sum((x-y).\hat{}2).\hat{}0.5$ ***Eq*(1)**

Where x and y are the feature vectors; *Fvec1* and *Fvec2* respectively originating from the two fingerprint samples to be compared.

Matching score = $\frac{1}{(1+Ed)}$ ***Eq*(2)**

Where *Ed* is the Euclidean distance between the two feature vectors; *Fvec1* and *Fvec2* respectively originating from the two fingerprint samples to be compared

Figure 4: Fingerprint Image Sample (Extracted from FVC2000-DB2-A)

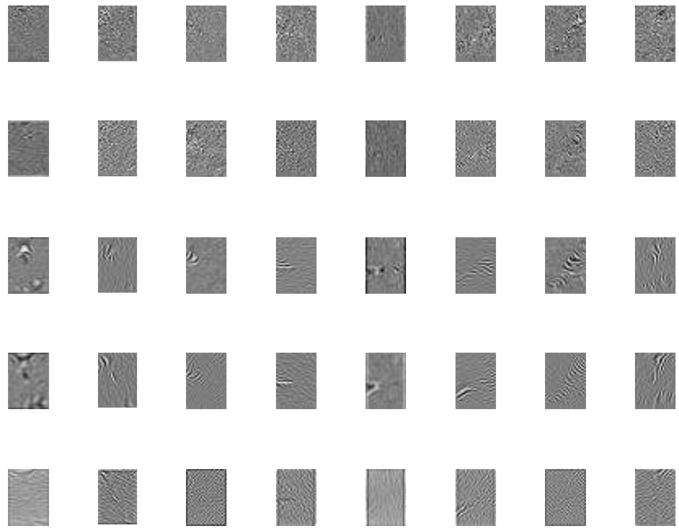

Figure 5: Real Parts of the Gabor Filters

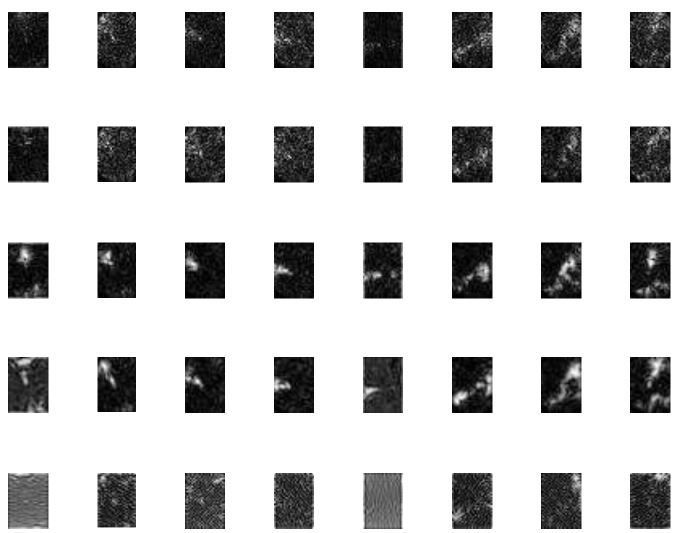

Figure 6: Magnitudes of the Gabor Filters

6.4 Implementation Environment, Fingerprint Database Used, Matching methods used and Experimental Setup

A description of the implementation environment, the fingerprint databases used, the matching methods used and the setup of all experiments is provided for in Chapter three.

6.5 Results and Discussions

This section presents the results, their discussion and the anticipated future work.

6.5.1 Results

6.5.1.1 Experiments on the FVC2000-DB2-A Fingerprint Database

For this database, four permutation sets (Set1, Set2, Set3, and Set4) were formulated for multi-sample enrollment and single-sample genuine verification as well impostor verification. For each permutation set in both the minutiae-based method and the Gabor Filter-Based method, a multi-sample enrollment and single-sample verification was performed to check the recognition performance improvements amongst the sets. In each set 400 genuine comparisons and 9900 impostor comparisons were generated. For the whole multiple enrollment experiments in both the minutiae-based method and the Gabor Filter-Based method, 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons were generated. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set for both the minutiae-based method and the Gabor Filter-Based method are shown in Table 10.

6.5.1.2 Experiments on the FVC2006-DB2-A Fingerprint Database

For this database, six permutation sets (Set1, Set2, Set3, Set4, Set5 and Set6) were formulated for multi-sample enrollment and single-sample genuine verification as well impostor verification. For each permutation set in both the minutiae-based method and the Gabor Filter-Based method, a multi-sample enrollment and single-sample verification was performed to check the recognition performance amongst the sets. In each set 840 genuine comparisons and 19460 impostor comparisons were generated. For the whole multiple enrollment experiments in in both the minutiae-based method and the Gabor Filter-Based method, 140 x 6 x 6 = 5040 genuine comparisons and 140 x 139 x 6 = 116760 impostor comparisons were generated. The attained

Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set for both the minutiae-based method and the Gabor Filter-Based method are shown in Table 11.

6.5.1.3 Graphical Comparisons of Results from the FVC2000-DB2-A and FVC2006-DB2-A Fingerprint Database Experiments

This section provides graphical comparisons resulting from the experiments done on both fingerprint databases. Figure 7 and Figure 8 provide comparisons on recognition performance, Figure 9 and Figure 10; running time/speed comparisons, while Figure 11 and Figure 12 provide comparisons on memory consumption.

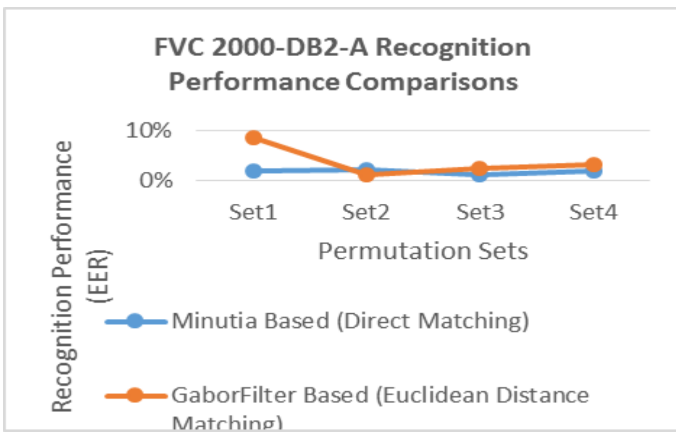

Figure 7: FVC 2000-DB2-A Recognition Performance Comparisons

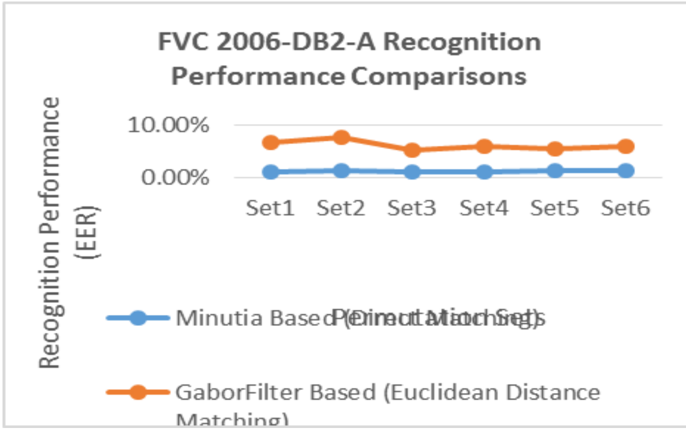

Figure 8: FVC 2006-DB2-A Recognition Performance Comparisons

Table 10: Summary of Experimentation Results on FVC 2000 DB2-A Database

FVC 2000-DB2-A	**Recognition Performance (EER)**		**Running Time /Speed (sec)**		**Peak Memory Consumption(KB)**	
Permutation Sets	**Minutiae-Based**	**Gabor Filter-Based**	**Minutiae-Based**	**Gabor Filter-Based**	**Minutiae-Based**	**Gabor Filter-Based**
Set1	2.00%	8.50%	337.01	1609.45	960	2696
Set2	2.25%	1.25%	235.38	1561.27	320	1892
Set3	1.25%	2.50%	231.75	1588.27	148	1892
Set4	2.00%	3.25%	232.82	1580.76	148	2084

Table 11: Summary of Experimentation Results on FVC 2006 DB2-A Database

FVC 2006-DB2-A	**Recognition Performance (EER)**		**Running Time /Speed (sec)**		**Peak Memory Consumption(KB)**	
Permutation Sets	**Minutiae-Based**	**Gabor Filter-Based**	**Minutiae-Based**	**Gabor Filter-Based**	**Minutiae-Based**	**Gabor Filter-Based**
Set1	0.95%	6.67%	594.58	13889.48	364	5536
Set2	1.19%	7.50%	593.40	13767.57	324	5404
Set3	1.07%	5.24%	723.78	10336.05	320	5024
Set4	0.95%	5.83%	704.87	10110.41	320	4828
Set5	1.19%	5.36%	622.81	10734.52	448	5216
Set6	1.19%	5.95%	547.95	10636.45	320	4896

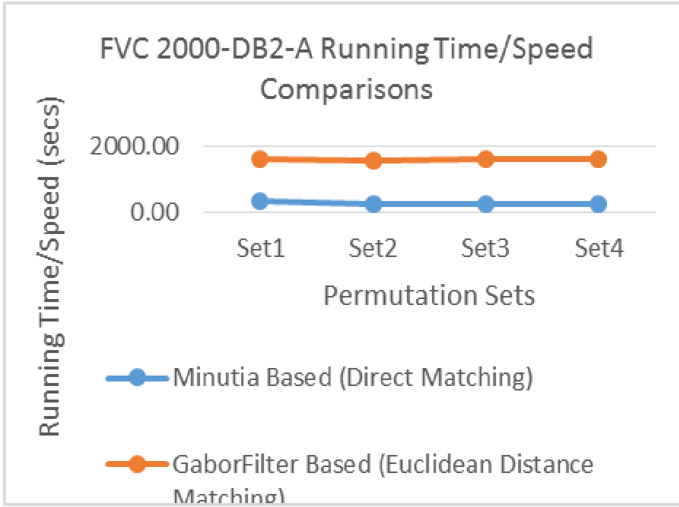

Figure 9: FVC 2000-DB2-A Running Time/Speed Comparisons

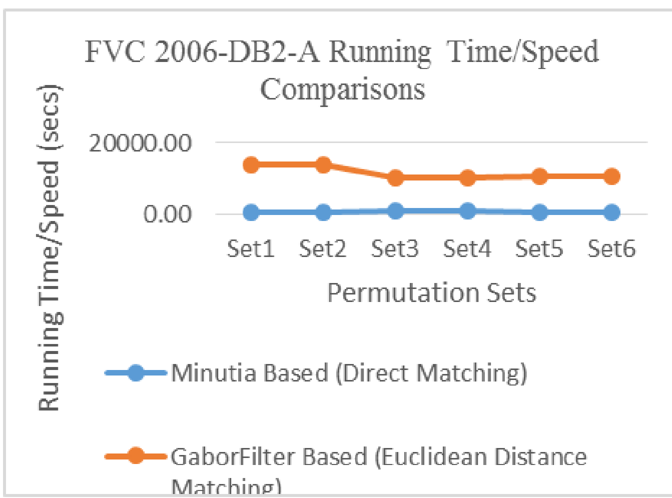

Figure 10: FVC 2006-DB2-A Running Time/Speed Comparisons

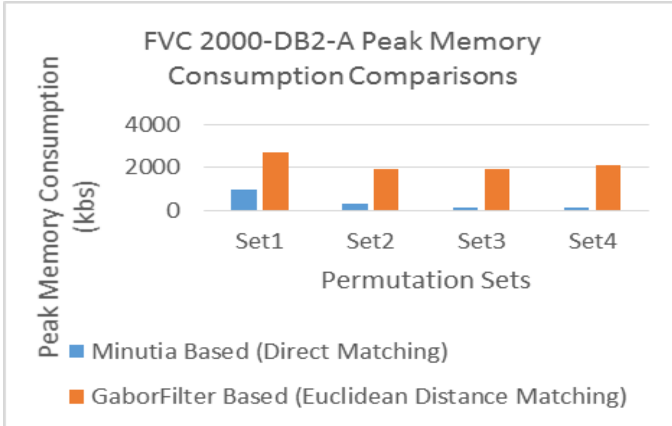

Figure 11: FVC 2000-DB2-A Peak Memory Consumption Comparisons

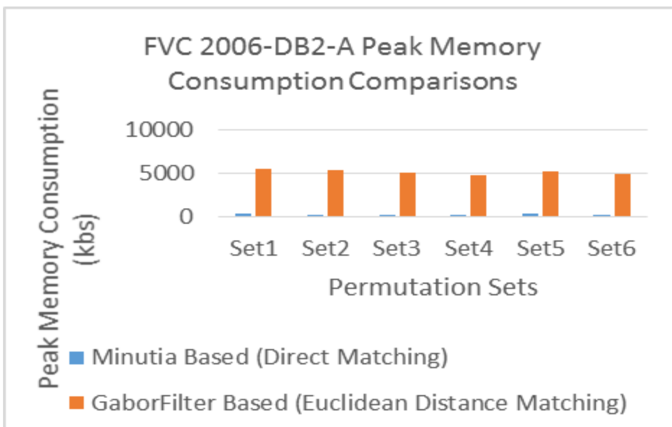

Figure 12: FVC 2006-DB2-A Peak Memory Consumption Comparisons

6.5.2 Discussions

Critically analyzing the results from both fingerprint databases as presented in Table 10 and Table 11, it can be observed that minutiae-based approaches are still superior in terms of generating a good recognition performance, a reduced matching speed and a reduced memory consumption when implemented in multiple enrollment fingerprint recognition systems for the above experiments that we setup. However, based on the same results, one can anticipate that Gabor filter-based methods have a promising future for implementation in multiple enrollment based fingerprint recognition systems. For instance, considering the results in Table 10, it can be observed that the recognition performance attained from experiments on Set2 in the FVC 2000-DB2-A fingerprint database under the Gabor filter-based method is far superior to that of the minutiae-based method.

A graphical illustration of the results as shown in Figures 7&8 for recognition performance, 9&10 for running time/speed and 11&12 for memory consumption; shows that the Gabor filter-based method has generally performed poorly with regards to recognition accuracy, running time/speed and memory consumption while the minutiae-based method performed better in all aspects. Based on the initial challenge identified in the minutiae based method as being difficult to extract all minutiae points from the fingerprint images, this already gives the minutiae method a less computation time/speed as well as a lower memory consumption; since the features to match are few. From the experiments, it was observed that templates under the minutiae-based method had few features extracted. On the other hand, the feature vectors generated from the Gabor filter-based method were so rich with many features extracted. One can therefore confidently argue that the many features contributed to the poor matching speed/running time as well as a higher memory consumption in the Gabor filter-based method.

It is however important to also note that in both methods the results are still not good enough as would be expected. This is attributed to the fact that there was no unique/additional advancement or tweaking performed onto the algorithms. In both cases (minutiae-based and Gabor filter-based), the algorithms match all the enrolled samples (i.e. whether good or bad) of an individual. This already puts an overhead to the matching speed as well as memory consumption; considering the fact that the more the images to match, the more time it takes and the more memory it consumes.

6.6 Conclusions

In this chapter the challenges faced by minutiae based matching approaches are introduced. It was found out that these approaches suffer the difficulty of automatically extracting all minutiae points due to failure to detect the complete ridge structures of a fingerprint. It was also noted that with poor quality fingerprint images, detection of minutiae points as well as describing all the local ridge structures was challenging hence also making it difficult to quickly match two fingerprints that have a difference in the number of unregistered minutiae. A Gabor filter-based method; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system, was experimented. This Gabor filter-based multiple enrollment fingerprint recognition method was compared with a spectral minutiae-based method using two fingerprint databases; FVC 2000-DB2-A and FVC 2006-DB2-A. Although the minutiae-based method outperformed the proposed Gabor filter-based method, the results attained from the later were promising and a good basis for improvement to implement Gabor filter-based techniques while designing multiple enrollment based fingerprint systems. This was a motivation to further improve recognition performance, running time/matching speed and reduce memory consumption in Gabor filter-based multiple enrollment based fingerprint recognition systems as discussed in the next Chapter (seven).

With respect to research question three of this thesis that was formulated in Section 1.4, this Chapter addressed objective number two, three and four by providing a Gabor filter-based method, the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. A Gabor filter-based multiple enrollment based fingerprint recognition system was designed, implemented (simulated), tested and results presented.

The contribution of this chapter is a Gabor filter-based fingerprint recognition system design method; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system.

CHAPTER SEVEN: ENHANCED GABOR FILTER BASED FINGEPRINT RECOGNITION

This chapter presents an enhanced/improved non-minutiae fingerprint matching technique; Combined Feature Level and Score Level Fusion Gabor filter-based approach, the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. Section 7.1 of this chapter introduces the challenges faced by minutiae based matching approaches, Section 7.2 provides the related work/literature while Section 7.3 presents the designed Combined Feature Level and Score Level Fusion Gabor-filter based multiple enrollment matching. The designed approach first extracts Gabor features from all input fingerprint image sample, creates column vectors of the extracted features, normalizes them to zero mean and unit variance and finally stores them with unique identifications (IDS). A random feature level fusion of the feature vectors generated from the different fingerprints is performed. Two feature vectors are concatenated and feature selection done in preparation for final matching/comparison. It is at this stage after feature selection that multiple enrollment and single sample verification is done. Direct matching then follows calculating the Euclidean distance between the two newly fused feature vectors originating from the two randomly fused feature vectors of the fingerprint samples to be compared. It is from this Euclidean distance value obtained that a matching score is computed and standardized. An explanation of how the experiments were setup, the databases and methods used together with the environment in which they were implemented is provided in Chapter three. In Section 7.5 through 7.6, the results are presented, their discussion and comparisons made and finally, conclusions drawn respectively.

7.1 Background

In our previous work [121], it was noted that a number of researchers have concentrated on minutiae-based matching methods while setting up multiple enrollment based fingerprint recognition systems. Matching methods such as correlation based like, [110], [111], [112], [113], [114] and pattern based methods like, [22], [94], [95] have been generally used for verification, indexing and identification in fingerprint recognition; but rarely implemented in multiple enrollment based fingerprint recognition systems. The challenges of minutiae-based matching methods as pointed out in [69] were; difficulty in automatically extracting all minutiae points due to the failure to detect the complete ridge structures of a fingerprint, as well as describing all the local ridge structures as minutiae points. These make matching a difficult process for example the case where two fingerprints have different numbers of uncaptured minutiae points. A non-minutiae based technique (Gabor filtering) which is known to be rich in terms of distinguishing features and an alternative since it captures both the local and global details in a fingerprint was proposed. Its resultant representation is scale, translation and rotation invariant and it produces short fixed length feature vectors, which makes them appropriate for indexing, faster fingerprint matching and storage on smaller devices [76]. The above mentioned, was the first of the kind to implement a Gabor Filter-Based verification multiple enrollment based fingerprint recognition system. Although the minutiae-based method outperformed the proposed Gabor filter-based method in the previous work, the results attained from the later were promising for implementation and helpful in designing multiple enrollment based fingerprint systems. However, there were still challenges in the proposed approach; the recognition performance was still poor, the matching speed/running time was bad and memory consumption was at the worst.

This chapter presents an enhanced technique; a combined feature level and score level fusion Gabor filter-based approach; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. The combined feature level and score level fusion technique greatly improves the recognition performance, the running time/matching speed and reduces the memory consumption.

7.2 Related Work

Fusion in biometrics has been applied in fingerprint recognition systems since long [10]. Fusion takes on various forms depending on the choice of the source of information made [40]. One of the commonly used forms of fusion is the combination of multiple traits; for example, fingerprint and face, fingerprint and voice [22], [65], fingerprint and iris, fingerprint and hand geometry[32], face and speech [63, 117 ,71], face, fingerprint and hand geometry [60] and many more. It is noted that fusion of fingerprints with other biometric traits not only results in a higher recognition accuracy but also adds on the security of the system. It becomes more robust to imposter attacks, difficult to fool and it also works as a substitute where a user may not have a certain biometric hence qualifying multiple traits biometric a good choice. The other commonly used form of fusion is combining multiple fingers of the same person like in [74]. In the multiple traits fusion form, the comments levels of fusion that have been used are score and rank levels because of the difference in representation among the traits [10]. For the multiple finger form of fusion, score level fusion has been commonly implemented. The approach in this paper uses a combination of feature level and score level fusion based on multiple instances of the same biometric trait (fingerprint) to overcome such challenges. Feature level fusion can help to prevent modification of the biometric template since it is not only one feature but a combination of random features which the attacker may not be able to tell.

Feature level fusion has been deployed by a number of researchers to improve recognition performance in multimodal/multibiometric systems. Arun and Rohin in [122], [123], use feature level fusion to fuse hand and face biometrics, Dakshina et al in [124] fused fingerprint and ear biometrics to attain a robust performance while A. Rattani et al in [125] also used feature level fusion to fuse face and fingerprint biometrics to improve recognition accuracy. Adams and David in [126] applied feature level fusion on multiple Gabor filters to produce a single fused feature which on comparison/matching using normalized hamming distance improved efficiency in identifying individual's palmprints. Adams et al [127], further made improvements in verification and identification when they fused multiple elliptical Gabor filters of a palmprints using feature level fusion. Poonam and Zope [128], used Gabor filter based multimodal biometric system where they use feature level fusion to fuse fingerprint and face Gabor filters to reduce computational complexity but improve accuracy. Gayathri and Ramamoorthy [129] use feature level fusion to fuse Gabor texture from palmprint and iris to improve recognition accuracy. Fathima and Poornima [130] use feature level fusion to fuse iris and ear features performance in their multimodal biometric authentication system. Navdeep and Gaurav [131] also fuse palmprint and fingerprint using feature level fusion to obtain a better system recognition performance. Jacob et al [132] use feature level fusion to fuse features extracted from one modality/same biometric trait (multiple fingerprints) of an individual to obtain an improvement in matching performance/processing time. N. Vinay Kumar et al [133], Use feature level fusion for classifying many logos to achieve a more accurate classification compared to a single logo feature. The Euclidian distance between the test logos and stored logos is calculated and the minimum Euclidian distance amongst all is used to classify the logo image as a member of the class. Other researchers like [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144] and [145], have also used feature level fusion to improve recognition performance in multimodal biometric systems. The analysis shows that feature level fusion has picked up interest from various researchers as compared to before when score level fusion and decision level fusion were the most commonly used. It has also been noted that most of the researchers have concentrated on multiple traits while using feature level fusion. These approaches suffer incompatibility due to difference in feature sets, feature space and feature vector length [31] making it challenging to fuse or even to trust those fused feature vectors that result from padding to make the feature vector lengths similar. The new approach uses Gabor filters focusing on combining both feature level fusion and matching score level fusion using multiple instances of the same biometric trait (fingerprint).

7.3 Combined Feature Level and Score Level Gabor Filter-Based Multiple Enrollment Fingerprint Recognition

In this method, the Gabor features of all input fingerprint image samples are first extracted as in [99]. Column vectors consisting of the Gabor features of the input fingerprint image samples are created. These feature vectors are normalized to zero mean and unit variance (to remove any noise originating from sensors as well as the grey level background which maybe generated because of the finger pressure differences), and then stored with unique identification (ID) names. A random feature level fusion of the feature vectors generated from the different fingerprints is performed. Two feature vectors are concatenated and feature selection done in preparation for final matching/comparison (see algorithm Section 7.3.1). It is at this stage after feature selection that multiple enrollment and single sample verification is done. Direct matching is done by calculating the Euclidean distance (using Equation 1- *Eq1*) between the two newly fused feature vectors; originating from the two randomly fused fingerprint feature vectors. Based on this Euclidean distance(Ed) value obtained, a matching score is computed such that; the higher the Euclidean distance(*Ed*), the lower the matching score and vice versa. The score is computed and standardized as shown in Equation 2 (*Eq2*) [100]. Finally, score level fusion based on the Max Rule in [32] follows by taking the maximum score amongst the attained values.

Euclidean Distance(*Ed*) = $norm(x - y)$ **……………………………………..………….*Eq*(3)**

Where x and y are the randomly fused feature vectors; *fffv1* and *fffv2* respectively originating from the two fingerprint samples to be compared. The formula is a standard MATLAB function.

Matching score = $\frac{1}{(1+Ed)}$ **……………………………………..…………………………*Eq*(4)**

Where *Ed* is the Euclidean distance between the two randomly fused feature vectors; *fffv1* and *fffv2* respectively originating from the two fingerprint samples to be compared.

7.3.1 The Algorithm Used

Let ffvID_n = {ffv1_1, ffv1_2, ffv1_3,…, ffv1_n} represent an individual's fingerprint feature vectors; where (i) ffvID = 1:100 and n = 1:8, are the feature vectors (ffv) extracted from 100 individuals (IDs) 8 copies each for FVC 2000-DB2-A database and (ii) ffvID = 1:140 and n = 1:12; are feature vectors (ffv) extracted from 140 individuals (IDs) 12 copies each, for the FVC 2006-DB2-A database. The fused fingerprint feature vector fffvID_n = {fffv1_1, fffv1_2, fffv1_3 … fffv1_n} is obtained by concatenating two fingerprint feature vectors and performing feature selection to obtain the final fused feature vector. Table 12 and Table 13 represent sample feature level fusion for one individual in both databases respectively.

Table 12: Sample feature level fusion for one individual (ID=1) in the FVC 2000-DB2-A database

Fingerprint Feature Vector	**Randomly Selected Fingerprint Feature Vector**	**Fused Fingerprint Feature Vector**
ffv1_1	ffv1_2	fffv1_1
ffv1_2	ffv1_3	fffv1_2
ffv1_3	ffv1_4	fffv1_3
ffv1_4	ffv1_5	fffv1_4
ffv1_5	ffv1_6	fffv1_5
ffv1_6	ffv1_7	fffv1_6
ffv1_7	ffv1_8	fffv1_7
ffv1_8	ffv1_1	fffv1_8

Table 13: Sample feature level fusion for one individual (ID=1) in the FVC 2006-DB2-A database

Fingerprint Feature Vector	**Randomly Selected Fingerprint Feature Vector**	**Fused Fingerprint Feature Vector**
ffv1_1	ffv1_2	fffv1_1
ffv1_2	ffv1_3	fffv1_2
ffv1_3	ffv1_4	fffv1_3
ffv1_4	ffv1_5	fffv1_4
ffv1_5	ffv1_6	fffv1_5
ffv1_6	ffv1_7	fffv1_6
ffv1_7	ffv1_8	fffv1_7
ffv1_8	ffv1_9	fffv1_8
ffv1_9	ffv1_10	fffv1_9
ffv1_10	ffv1_11	fffv1_10
ffv1_11	ffv1_12	fffv1_11
ffv1_12	ffv1_1	fffv1_12

7.4 Implementation Environment, Fingerprint Database Used, Matching methods used and Experimental Setup

A description of the implementation environment, the fingerprint databases used, the matching methods used and the setup of all experiments is provided for in Chapter three

7.5 Results and Discussions

In this section, the authors present the results, their discussion and the future work.

7.5.1 Results

7.5.1.1 Experiments on the FVC2000-DB2-A Fingerprint Database

For this database, four permutation sets (Set1, Set2, Set3, and Set4) were formulated for multi-sample enrollment and single-sample genuine verification as well impostor verification. For each permutation set in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, the researchers performed a multi-sample enrollment and single-sample verification to check the recognition performance amongst the sets. In each set 400 genuine comparisons and 9900 impostor comparisons were generated. For the whole multiple enrollment experiments in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons were generated. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set for both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method are shown in Table 14.

7.5.1.2 Experiments on the FVC2006-DB2-A Fingerprint Database

For this database, six permutation sets (Set1, Set2, Set3, Set4, Set5 and Set6) were formulated for multi-sample enrollment and single-sample genuine verification as well impostor verification. For each permutation set in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, a multi-sample enrollment and single-sample verification was performed to check the recognition performance amongst the sets. In each set 840 genuine comparisons and 19460 impostor comparisons were generated. For the whole multiple enrollment experiments in in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, 140 x 6 x 6 = 5040 genuine comparisons and 140 x 139 x 6 = 116760 impostor comparisons were generated. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set for both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method are shown in Table 15.

7.5.1.3 Graphical Comparisons of Results from the FVC2000-DB2-A and FVC2006-DB2-A Fingerprint Database Experiments

In this section, the graphical comparisons resulting from the experiments done on both fingerprint databases are presented. Figure 13 and Figure 14 provide comparisons on recognition performance, Figure 15 and Figure 16; running time/speed comparisons, while Figure 17 and Figure 18 provide comparisons on memory consumption.

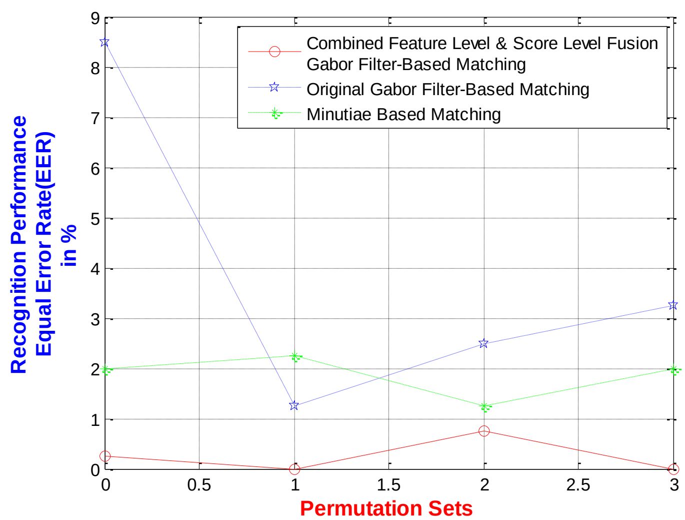

Figure 13: FVC 2000-DB2-A Recognition Performance Comparisons

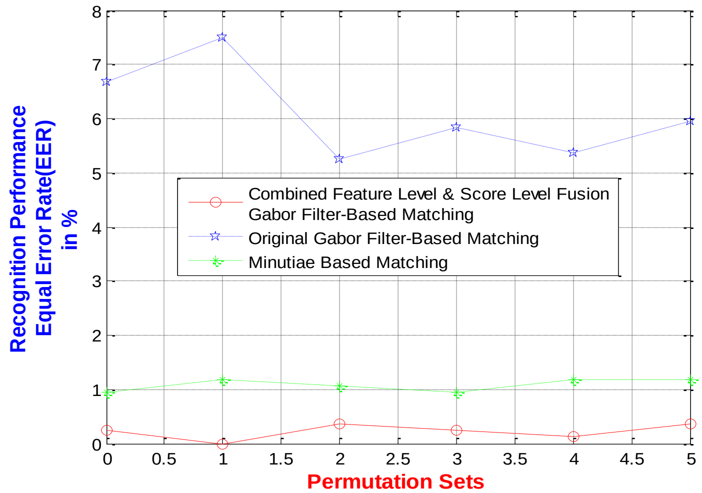

Figure 14: FVC 2006-DB2-A Recognition Performance Comparisons

Table 14: Summary of Experimentation Results on FVC 2000 DB2-A Database

FVC 2000-DB2-A	**Recognition Performance (EER) %**			**Running Time /Speed (Secs)**			**Peak Memory Consumption (kbs)**		
Permutation Sets	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter-Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter-Based**
Set1	2.00%	8.50%	0.26%	337.01	1609.45	5.29	960	2696	44
Set2	2.25%	1.25%	0.00%	235.38	1561.27	5.41	320	1892	44
Set3	1.25%	2.5%	0.76%	231.75	1588.27	5.30	148	1892	64
Set4	2.00%	3.25%	0.00%	232.82	1580.76	4.59	148	2084	40

Table 15: Summary of Experimentation Results on FVC 2006 DB2-A Database

FVC 2006-DB2-A	**Recognition Performance (EER) %**			**Running Time /Speed (Secs)**			**Peak Memory Consumption (kbs)**		
Permutation Sets	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter-Based**
Set1	1.00%	6.70%	0.24%	594.58	13889.48	20.62	364	5536	64
Set2	1.19%	7.50%	0.00%	593.40	13767.57	15.49	324	5404	40
Set3	1.07%	5.20%	0.37%	723.78	10336.05	22.88	320	5024	44
Set4	1.00%	5.83%	0.24%	704.87	10110.41	20.88	320	4828	40
Set5	1.00%	5.40%	0.12%	622.81	10734.52	14.21	448	5216	44
Set6	1.19%	5.95%	0.36%	547.95	10636.45	17.00	320	4896	64

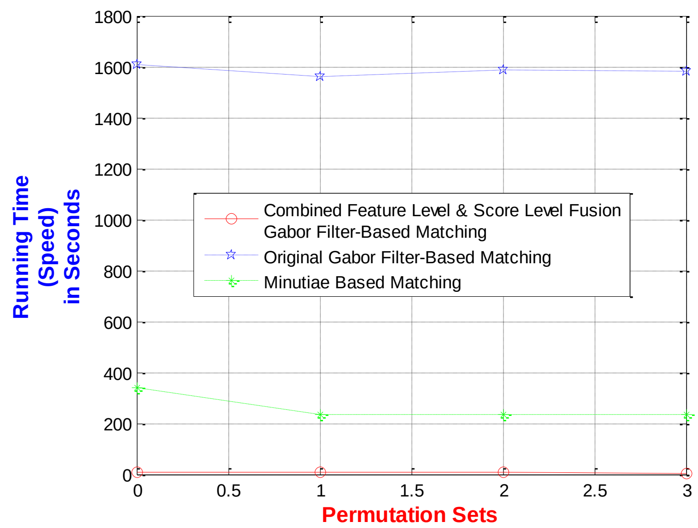

Figure 15: FVC 2000-DB2-A Running Time/Speed Comparisons

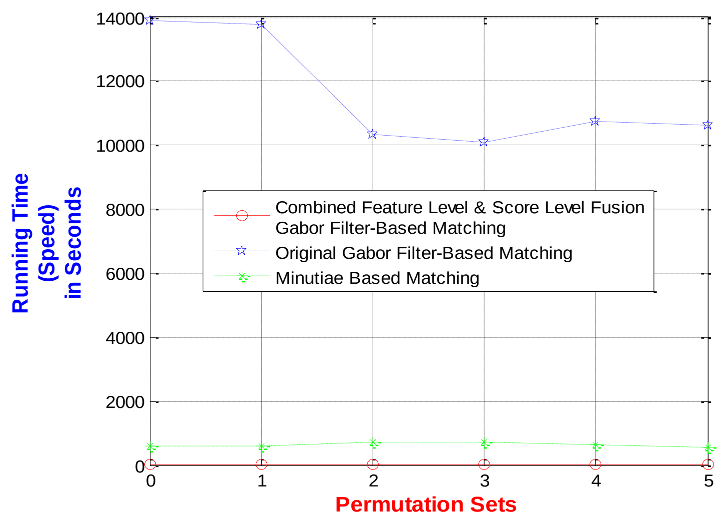

Figure 16: FVC 2006-DB2-A Running Time/Speed Comparisons

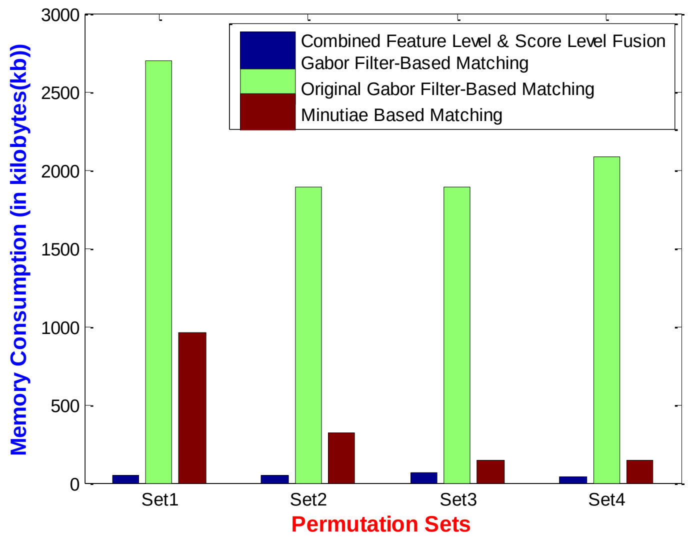

Figure 17: FVC 2000-DB2-A Peak Memory Consumption Comparisons

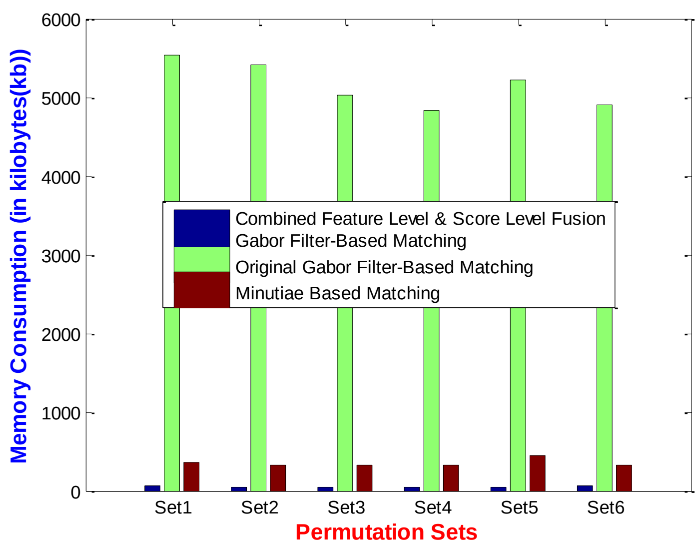

Figure 18: FVC 2006-DB2-A Peak Memory Consumption Comparisons

7.5.2 Discussions

An analysis of results emanating from both fingerprint databases as presented in Table 14 and Table 15, shows that the combined feature level and Score Level fusion Gabor filter-based matching approach outperforms all the other approaches in terms of generating a good recognition performance, a reduced matching speed and a reduced memory consumption when implemented in multiple enrollment fingerprint recognition systems. A deeper analysis of the same results indicates that there is a significant percentage increase brought about by the combined feature level and Score Level fusion Gabor filter-based matching approach in comparison to the famous minutiae-based matching approach. The percentage increases in the FVC 2000-DB2-A are 86.45%, 98.01% and 87.82%, while those in the FVC 2006-DB2-A are 79.71%, 97.07% and 85.88% respectively for recognition performance improvement, matching speed improvement and memory consumption reduction. Therefore, the combined feature level and Score Level fusion Gabor filter-based matching approach significantly out competes the minutiae-based matching approach in this case.

It is also evident in figures 13&14 for recognition performance, 15&16 for running time/matching speed and 17&18 for memory consumption that the combined feature Level and Score Level fusion Gabor filter-based method has performed extremely well with regards to recognition accuracy, running time/matching speed and memory consumption. The good performance of the combined feature Level and Score Level fusion Gabor filter-based method is attributed to a three core reasons that is: (i) during the feature level fusion, there was feature selection which was based on the good features amongst the two selected fingerprints hence generating a good final fused feature vector, (ii) there was also score level fusion performed after feature level fusion to further improve performance by taking the maximum/best scores after matching and lastly (iii) is the fact that the feature vectors generated are light making it easy to match them at a faster speed.

The features mentioned above as provided by the combined feature Level and Score Level fusion Gabor filter-based method are a good state of the art for implementation in real world applications for better recognition performance, good matching speed and reduced memory consumption.

7.6 Conclusion

In this chapter the challenges faced by minutiae based matching approaches are introduced. It was realized that these approaches suffer the difficulty of automatically extracting all minutiae points due to failure to detect the complete ridge structures of a fingerprint. It was also noted that with poor quality fingerprint images, detection of minutiae points as well as describing all the local ridge structures was hard hence also making it difficult to quickly match two fingerprints that had a difference in the number of unregistered minutiae. In our recent work in chapter six a Gabor filter-based method was proposed to realize its effect in multiple enrollment based fingerprint recognition systems. The results were seen to be poor but promising. This chapter provides an improved approach; the Combined Feature Level and Score Level Fusion Gabor filter-based method, which is still the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. The Combined Feature Level and Score Level Fusion Gabor filter-based multiple enrollment fingerprint recognition method was compared with the spectral minutiae-based method using two fingerprint databases; FVC 2000-DB2-A and FVC 2006-DB2-A. The attained results indicate that there is a significant percentage increase in recognition performance improvement, matching speed improvement and memory consumption reduction brought about by the combined feature level and Score Level fusion Gabor filter-based matching approach in comparison to the famous minutiae-based matching approach. The outstanding results attained from the designed approach possess good and recommendable features for future implementation and deployment in real world multiple enrollment fingerprint recognition applications that require better recognition performance, good matching speed and reduced memory consumption.

With respect to research question three of this thesis that was formulated in Section 1.4, this chapter addresses objective number two, three and four by providing a Combined Feature Level and Score Level Fusion Gabor filter-based multiple enrollment fingerprint recognition method, the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. A Gabor filter-based multiple enrollment based fingerprint recognition system was designed, implemented (simulated), tested and results presented.

The contribution of this chapter is a Combined Feature Level and Score Level Fusion Gabor filter-based fingerprint recognition system design method; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system.

CHAPTER EIGHT: CONCLUSIONS AND RECOMMENDATIONS

This Chapter is a summary of the whole thesis. In Sections 8.1 conclusions are made, and Section 8.2 provides recommendations. A synopsis of the anticipated future work is provided in Section 8.3

8.1 Conclusions

The purpose of this research was to provide a novel multiple enrollment fingerprint recognition approach that would further improve recognition accuracy, the matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems. To achieve the goal of this research, we formulated three research questions which emanated from the overall question, "*How can multiple enrollment based fingerprint recognition systems be better designed*?". Below is the list of research questions with reference to the achieved results and conclusions.

8.1.1 Research Question One (RQ1)

RQ1: ***What are the current approaches being used in designing multiple enrollment based fingerprint recognition systems?***

This question was important to achieve research objective 1. Formative research was performed to find out the state of the art in design of multiple enrollment fingerprint recognition systems. This research question was addressed in chapter two.

The origin, history of use of fingerprints and their viability as a biometric were introduced. A two decades literature survey was carried out, where a total of 55 research papers representing the state of the art in multiple enrollment for fingerprint recognition before 2004 and until up-to-date, were examined with respect to approach methodology and experimentation results. The analysis showed that a lot of research that had been done relating to multiple enrollment mainly focused on combining multiple fingerprint matchers (algorithms) to achieve better recognition accuracy; rather than concentrating on single fingerprint matchers focusing on multiple enrollment of fingerprints. However, the urge to combine multiple sources of biometric information to improve recognition accuracy was observed to have continuously and periodically increased through the two decades. It was also noted that some of the researchers had implemented decision level fusion in fingerprint verification; whereas the majority had implemented score level fusion and others had tried to combine the two in certain cases. In the literature survey, few researchers had implemented feature level fusion in multiple enrollment based fingerprint recognition systems. The literature survey also showed that the analyzed recognition accuracies from the different researchers were still low, little research had concretely concentrated on improving the matching speed (execution time) of such multiple source based biometric systems, the usability, memory consumption as well as acceptability. It was also noted that researchers had not concretely recommended which fingerprint matching methods would perform best when multiple enrollment was deployed in real world application scenarios. The literature survey indicates that there was need for closer studies on the existing fingerprint biometric systems that use multiple sources of biometric information (concentrating mainly on multiple samples of fingerprints from many fingers of the same individual) to evaluate their performance (recognition accuracy), matching speed, acceptability, usability, and memory consumption. It also indicated that there was need to propose novel multiple enrollment fingerprint recognition approaches which would further improve recognition accuracy, the matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems. Analysis of other matching methods rather than only minutiae based ones was also an important way forward made.

In conclusion therefore, with respect to research question one, this thesis addressed objective number one by:

1. Providing a state of the art literature survey of multiple enrollment for fingerprint recognition.

2. Providing all the existing approaches that have been used in designing multiple enrollment based fingerprint recognition systems.

3. Providing the challenges in multiple enrollment fingerprint recognition as well as a way forward to designing multiple enrollment based fingerprint recognition systems.

These were important to derive requirements for answering research question two to be able to achieve the remaining research objectives. The output from this research question was a literature survey that serves as a quick overview of the state of the art in multiple enrollment for fingerprint recognition for the past two decades.

8.1.2 Research Question Two (RQ2)

RQ2: ***How can the design multiple enrollment based fingerprint recognition systems be improved to achieve better recognition accuracy/performance and matching speed, but reduce memory consumption?***

This research question aimed at achieving objectives 2, 3 and 4. After knowing the challenges and necessary requirements as was pointed out in the output of research question one, it was then possible to come up with different novel approaches that would yield better multiple enrollment fingerprint recognition systems. The novel approaches were designed and subsequent multiple enrollment fingerprint recognition system implemented (simulated) from the approaches to test and validate their efficiency and effectiveness.

This research question two was addressed in chapter four and chapter five.

In chapter four, the basic concept of multiple enrollment for fingerprint recognition to determine its viability and effectiveness in fingerprint recognition systems was introduced. A multiple enrollment algorithm was designed and used together with existing fingerprint recognition techniques to carry out an evaluation. An evaluation of multiple enrollment was done in comparison to single enrollment using two methods, (i) a Traditional minutiae based matching method and (ii) a Spectral Minutiae-based matching method. The evaluation was carried out on two fingerprint databases; SAS-DB2 and FVC2000-DB2 databases. The experimentation results and evaluations show that multiple enrollment as whole outperforms single enrollment. Multiple enrollment in experiment one improved the recognition performance by 83.33% from EER of 0.75% to EER of 0.13% with FVC2000-DB2 fingerprint database, and by 75.55% from EER of 1.14% to EER of 0.28% with the SAS-DB2 fingerprint database. On the other hand, the multiple enrollment in experiment two improved the recognition performance by 71.51% from EER of 6.14% to EER of 1.75% with the FVC2000-DB2 fingerprint database and improved recognition performance by 53.61% from EER of 14.97% to EER of 6.94% with SAS-DB2 fingerprint database. This was the very first attempt of carrying out multiple enrollment and therefore other aspects such as computational/matching speed and memory consumption were not considered. A comparison with single enrollment and other multiple enrollment results in literature (Section 2.5.1) shows that our algorithms were superior by over 38.1% (basing on the least attained EER) in terms of recognition performance.

As part of research question two, this work concentrated on recognition accuracy only and was an eye opener for the entire research process. A new multiple enrollment algorithm with improved recognition performance using a new fingerprint representation (minutiae spectrum) was designed. It was therefore a revelation that there was a possibility of attaining better results with subsequent multiple enrollment experiments.

Still with respect to research question two, in Chapter five, the challenges faced during fingerprint image capture were introduced. Also, the fact that the current multiple enrollment based fingerprint recognition systems studied still suffered poor matching speeds, a lot of memory consumption and the recognition accuracies were still very low hence making implementation in real-world applications difficult, was made known. A novel approach that performs prior selection of good fingerprint image samples of an individual for matching was designed to further improve recognition performance, reduce the matching speed as well as memory consumption. A spectral minutiae based matching method and two fingerprint databases (FVC2000-DB2 and FVC2006-DB2) were used. A comparison of our results with the existing ones presented in literature (Section 2.5.1) showed that they were more superior by over 29.6% with algorithm two (Alg2) and by 100% with algorithm three (*Alg3*). This therefore made us conclude that it was possible to design better multiple enrollment based fingerprint recognition systems with a high recognition accuracy, high matching speed and low memory consumption using our approach.

8.1.3 Research Question Three (RQ3)

RQ3: ***How would a particular fingerprint matching method/approach affect the design of multiple enrollment based fingerprint recognition systems in terms of recognition performance/accuracy improvement, matching speed improvement as well as reduction in memory consumption?***

This question also aimed at achieving objectives 2, 3 and 4. It was noted that there were three kinds of fingerprint matching methods one would implement in fingerprint recognition systems, although this research concentrated on only two. This research question was important in determining which method(s) would perform exceptionally when implemented in multiple enrollment fingerprint recognition systems. Knowing the best performing method(s) was important in expressing recommendations to designers of such systems. This process was still part of testing and evaluating the designed approach in this research.

Research question three was addressed in chapter six and seven

In chapter six, the challenges faced by minutiae based matching approaches were introduced. It was realized that these approaches suffered the difficulty of automatically extracting all minutiae points due to failure to detect the complete ridge structures of a fingerprint. It was also noted that with poor quality fingerprint images, detection of minutiae points as well as describing all the local ridge structures was difficult hence also making it difficult to quickly match two fingerprints that had a difference in the number of unregistered minutiae. A Gabor filter-based method; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system was designed. The Gabor filter-based multiple enrollment fingerprint recognition method was compared with a spectral minutiae-based method using two fingerprint databases; FVC 2000-DB2-A and FVC 2006-DB2-A. Although the minutiae-based method outperformed the proposed Gabor filter-based method, the results attained from the later were promising and were seen to be a good basis for implementing Gabor filter-based techniques in designing multiple enrollment based fingerprint systems. Therefore, as an output from this research question, a Gabor filter-based multiple enrollment based fingerprint recognition system was designed, implemented (simulated), tested and results presented

As part of research question three, this was a key motivation to further improve recognition performance, running time/matching speed and reduce memory consumption in Gabor filter-based multiple enrollment based fingerprint recognition systems. This improvement was addressed in Chapter seven.

Still respect to research question three, in Chapter seven a significant improvement was made to our previous work in Chapter six. In the previous work of Chapter six, a Gabor filter-based method had been proposed to realize its effect in multiple enrollment based fingerprint recognition systems. However, the results were seen to be poor but promising. An improved/enhanced approach; the Combined Feature Level and Score Level Fusion Gabor filter-based method was proposed, which was still the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. In this Combined Feature Level and Score Level Fusion Gabor filter-based multiple enrollment fingerprint recognition method, the Gabor features of all input fingerprint image samples were first extracted, Column vectors consisting of the Gabor features of the input fingerprint image samples created, normalized to zero mean and unit variance (to remove any noise originating from sensors as well as the grey level background which maybe generated because of the finger pressure differences), and then stored with unique identification (ID) names. A random feature level fusion of the feature vectors generated from the different fingerprints was performed. Two feature vectors were concatenated and feature selection was done in preparation for final matching/comparison. It was at this stage after feature selection that multiple enrollment and single sample verification was done. Direct matching was done by calculating the Euclidean distance between the two newly fused feature vectors; originating from the two randomly fused fingerprint feature vectors. Based on this Euclidean distance(Ed) value obtained, a matching score was computed such that; the higher the Euclidean distance(Ed), the lower the matching score and vice versa. The score was computed and standardized. Finally, score level fusion based followed by taking the maximum score amongst the attained values. Our new approach was compared with the spectral minutiae-based method using two fingerprint databases; FVC 2000-DB2-A and FVC 2006-DB2-A. The results indicated that there was a significant percentage increase in recognition performance improvement, matching speed improvement and memory consumption reduction brought about by the combined feature level and Score Level fusion Gabor filter-based matching approach in comparison to the famous minutiae-based matching approach. The percentage increases in the FVC 2000-DB2-A fingerprint database were 86.45%, 98.01% and 87.82%, while those in the FVC 2006-DB2-A fingerprint database were 79.71%, 97.07% and 85.88% respectively for recognition performance improvement, matching speed improvement and memory consumption reduction. The results attained from the approach above were outstanding and are therefore a proposed possibility for future deployment in real world multiple enrollment fingerprint recognition applications that require better recognition performance, better matching speed and a reduced memory consumption..

The argument of which matching method would perform best in multiple enrollment based fingerprint recognition systems cannot be concisely reached. An analysis of the combined feature level and Score Level fusion Gabor filter-based matching approach shows that it outperformed its counterpart the minutiae matching method. The algorithms were robust, the Gabor feature vectors were practically light (in terms of size and weight); making it easy to match them, consuming less memory and hence fit for both resource constrained real applications and devices (such as mobile smart phones, tablets, etc) and those that are not resource constrained. For our recommendation, one would better implement this approach in real world applications than the minutiae approach if they were to achieve robustness, high recognition accuracy, and better matching speed and reduced memory consumption. However, we find it impartial to overrule that the combined feature level and Score Level fusion Gabor filter-based matching approach is the best. This is because, we give an allowance of the same possibilities of combining feature level and Score Level fusion in the Minutiae-based matching approach to observe the outcome. However not forgetting the fact that minutiae matching methods still face a problem of detecting minutiae points from poor quality fingerprint images and the minutiae templates are also heavy and cannot easily be implemented in resource constrained applications and devices.

8.2 Recommendations and Future Work

8.2.1 Recommendations

The advanced spectral minutiae based multiple enrollment algorithms presented in Chapter four of this thesis can be used in designing multiple enrollment based fingerprint recognition systems that are to be used in environments with enough and good computing resources such as: good fingerprint scanners/readers, high processing power and enough computational memory. The fingerprint images also need to be of good quality. Recommendations for implementing the spectral minutiae based multiple enrollment algorithms in resource constrained real world applications and devices are reserved. This is because minutiae based matching methods still face a problem of detecting minutiae points from poor quality fingerprint images and the minutiae templates are also heavy and cannot easily be implemented in resource constrained real world applications and devices. Devices such as mobile smart phones, tablets, and any other smaller portable devices, may not achieve the best output when such algorithms are implemented. Implementation in such devices would require extra efforts and cleverness as explained in section 8.1 above.

The combined feature level and Score Level fusion Gabor filter-based algorithms presented in this thesis performed well, were robust and can be used to design multiple enrollment based fingerprint recognition systems for all categories of environments; i.e., resource enabled environments (ones with the necessary resources) and resource constrained environments. It has already been argued that these algorithms are robust, the Gabor feature vectors were practically light (in terms of size and weight); which made it easy to match them, consuming less memory and hence fit for both resource constrained real applications and devices (such as mobile smart phones, tablets, etc.) and those that are not resource constrained.

Generally, the recommendation from this work is that, to benefit from the concept of multiple enrollment use in real world applications, developers need to implement with extra cleverness as provided for in this thesis.

8.2.2 Future Work

This thesis has addressed the challenges concerning the design and development of multiple enrolment based fingerprint recognition systems. Below are the proposed number of ways in which this research can be extended:

Researchers can study ways of combining feature level and score level fusion for the minutiae-based matching methods. It is anticipated that the results will surely be good basing on the experience of observations in the combined feature level and score level fusion for the Gabor filter-based matching method.

Other studies can also try to deploy classification techniques such as k-Nearest Neighbor (KNN) classifier or the Support Vector Machines (SVM) classifier to further improve on the matching of the feature vectors to attain a better recognition performance, matching speed and reduce memory consumption for both minutiae based techniques and non-minutiae based techniques.

Future work can also look into a combined approach of using both minutiae-based methods and Gabor filter-based methods and assess the implication of deployment in multiple enrollment based fingerprint recognition systems. Such an approach may bring about a good performance but may affect memory consumption because of the many features templates to be stored.

Throughout all the experiments, there was no consideration of securing the multiple templates. The security of the multiple templates can also be an interesting research area to venture since a lot of research has concentrated on security of single templates in single enrollment fingerprint recognition systems.

Multiple enrollment is not only fit for fingerprint recognition. This is an interesting technique that can also be implemented in other biometrics fields such other face recognition, ear recognition, palm print recognition, and many others. However, most of the other biometric traits require a lot of storage and computational resources in place.

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APENDICES

A. Appendix 1: List of Laboratories Working On Multiple Enrollment For Fingerprint Recognition

1. Biometric System Laboratory (University of Bologna)
2. Pattern Recognition and Image Processing Laboratory (Michigan State University)
3. Biometric Test Center (San Jose State University)
4. Biometric Recognition Group - ATVS (Universidad Autonoma de Madrid)
5. Sandia National Laboratories, USA
6. Multimedia Signal Processing and Security Lab, University of Salzburg (Austria),
7. Center for Mathematics and Scientific Computing, National Physical Laboratory NPL, UK
8. Information Technology Laboratory ITL, National Institute of Standards and Technology (NIST), USA
9. The FBI Laboratory, USA
10. Pattern Recognition and Applications Lab, University of Cagliari (Italy)

B. Appendix 2: Work plan and Timeframe

ACTIVITY PLANNED/ MONTH	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT
YEAR ONE 2013/2014												
Feasibility Study and information gathering												
Concept Paper Development/Submission												
Literature (Related Work) Search and gathering												
Proposal Development/Submission												
Experiment One Setup and implementation												
1st Research Article Writing/Submission												
2nd Research Article Writing/Submission												
Progressive Report writing/Submission												
Proposal Defense												
Experiment Two Setup and implementation												
3rd Research Article content compilation												
Progressive Report writing/Submission and Year Two Plan Review												

ACTIVITY PLANNED/ MONTH	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT
YEAR TWO 2014/2015												
3rd Research Paper writing/submission												
Experiment Three Setup and implementation												

4th Research Article content compilation												
4th Research Article writing/submission												
Progressive Report writing/Submission and Year Three Plan Review												
ACTIVITY PLANNED/ MONTH	**NOV**	**DEC**	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**
YEAR THREE 2015/2016												
Verification Experiment Setup and implementation												
5th Research Article content compilation												
5th Research Article writing/submission												
PhD Thesis content compilation												
PhD Thesis content Writing and Submission												
PhD Thesis Presentation Preparation												
PhD Defense												

C. Appendix 3: Research Ethics Committee Approval

MBARARA UNIVERSITY OF SCIENCE AND TECHNOLOGY
RESEARCH ETHICS COMMITTEE
P.O. Box 1410, Mbarara, Uganda. Tel: +256 4854 33795.,
E-mail: sec.rec@must.ac.ug Fax: +256 4854 20782

Our Ref: MUREC 1/7 **Date:** February 22, 2016

Mr. Fred Kaggwa
Institute of Computer Science
MUST

Re: **SUBMITTED PROTOCOL ON "DESIGN OF MULTIPLE ENROLMENT BASED FINGERPRINT RECOGNITION SYSTEMS" NO. 16/09-15**

Reference is made to the above protocol which was resubmitted to the Research Ethics Committee for reconsideration. The issues raised have been addressed.

I am pleased to inform you that your study has been approved for a period of one year up to February 22, 2017.

The following documents have been approved with the application:

Document	Language	Version
Proposal	English	Version 2
Protocol form	English	Version 2
Data Collection tools	English	Version 2

You are required to register the study with Uganda National Council for Science and Technology, and submit progress and end of study reports to MUST REC.

You may now proceed with the rest of the research activities after getting permission from Uganda National Council for Science and Technology.

Sincerely,

Dr Francis Bajunirwe
CHAIR,
MUST RESEARCH ETHICS COMMITTEE

D. Appendix 4: UNCST Approval

Uganda National Council for Science and Technology

(Established by Act of Parliament of the Republic of Uganda)

UNCST

Our Ref: **HS 2080**

27th July 2016

Kaggwa Fred
Principal Investigator
Mbarara University of science and Technology
Mbarara

Re: Research Approval: Design of Multiple Enrollment Based Fingerprint Recognition Systems

I am pleased to inform you that on **27/06/2016**, the Uganda National Council for Science and Technology (UNCST) approved the above referenced research project. The Approval of the research project is for the period **27/06/2016** to **27/06/2018**.

Your research registration number with the UNCST is **HS 2080.** Please, cite this number in all your future correspondences with UNCST in respect of the above research project.

As Principal Investigator of the research project, you are responsible for fulfilling the following requirements of approval:

1. All co-investigators must be kept informed of the status of the research.
2. Changes, amendments, and addenda to the research protocol or the consent form (where applicable) must be submitted to the designated Research Ethics Committee (REC) or Lead Agency for re-review and approval **prior** to the activation of the changes. UNCST must be notified of the approved changes within five working days.
3. For clinical trials, all serious adverse events must be reported promptly to the designated local REC for review with copies to the National Drug Authority.
4. Unexpected events involving risks to research subjects/participants must be reported promptly to the UNCST. New information that becomes available which alters the risk/benefit ratio must be submitted promptly for UNCST review.
5. Only approved study procedures are to be implemented. The UNCST may conduct impromptu audits of all study records.
6. A progress report must be submitted electronically to UNCST within four weeks after every 12 months. Failure to do so may result in termination of the research project.

Below is a list of documents approved with this application:

	Document Title	Language	Version	Version Date
1.	Research Proposal	English	N/A	March 2016

Yours sincerely,

Hellen. N. Opolot
For: Executive Secretary
UGANDA NATIONAL COUNCIL FOR SCIENCE AND TECHNOLOGY

cc: Chair, Mbarara University of Science and Technology, Research Ethics Committee

LOCATION/CORRESPONDENCE

Plot 6 Kimera Road, Ntinda
P. O. Box 6884
KAMPALA, UGANDA

COMMUNICATION

TEL: (256) 414 705500
FAX: (256) 414-234579
EMAIL: info@uncst.go.ug
WEBSITE: http://www.uncst.go.ug