Influence of Walking Surfaces and Speeds on Accelerometer-Based Gait Recognition

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To my most loved ones

ALLAH the Almighty

Muhammad (P.B.U.H)

My Parents

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Muhammad Muaaz, August 29, 2011

Abstract

Identification and verification is first line of defence of every secure system. Due to the advancement of technology and miniaturization, the use of mobile devices is highly increased since last decade. Nowadays, mobile phones are more powerful than the computers of early days of last decade. Today, mobile phones hold a lot of personal and sensitive data, which must be protected using most reliable, robust, convenient and cost effective authentication mechanisms.

Biometric authentication is one of the three methods of identification. Gait authentication is one type of biometric authentication that operates on behavioral characteristics of human beings. There are different approaches in gait authentication. In this thesis, we have used wearable sensor based approach and for this purpose Google G1 smart phone is used to collect gait data. This thesis is an attempt to find out the influence of different walking speeds (slow, normal and fast) and surfaces (flat carpeted, grass, gravel and inclined) on gait recognition. This gait data is collected from 48 subjects for these six different walk settings in two sessions on different days to measure same day and cross day performance. Later, different mathematical and machine learning concepts are used to analyze recorded data and extract typical gait cycle for each subject. Different evaluations are conducted to find out best parameter settings of these methods.

For different walking speeds, same-day results vary between 14% to 29%, and cross day results vary between 29% and 35%. Similarly, for different walking surfaces, same-day results vary between 9.78% to 39%, and cross day results vary between 28% to 42%. Results of tests conducted for one walk setting clearly reflects that slight change in parameters also influences the results.

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Chapter 1

Introduction

Identification of people is not a new problem and for ages mankind has developed and used different methods to identify and authenticate people by using face, voice, signature, keystrokes, hand geometry and fingerprints, etc. [41]. Reliable authentication has become an important task for many activities, such as performing financial transactions, access control, surveillance and healthcare [95].There are three different ways to authenticate people. i) knowledge-based, which means the user knows the password ii) token-based, which means the user have some kind of hardware which he uses for authentication purposes and iii) biometric, where a user uses his physiological or behavioral characteristics for authentication purposes.

1.1 Topic and Context

Gait recognition is a new dimension in biometric authentication. This thesis will focus on the gait as a biometric authentication system. In last decade gait recognition has become an active research area. Reason behind it's popularity is, unobtrusive nature of gait recognition. This allows to capture biometric samples without user's knowledge or interaction. In last 18 years most of the work done on gait authentication was video-based and mainly used for surveillance purposes. For instance, recognizing a fraud individual from the video camera. In the same era, door mats with sensors placed inside were also used for access control purposes. In 2005, for the first time the idea of utilizing acceleration produced as a result of the human walk for authentication purpose came across. This acceleration is recorded using an "*accelerometer sensor*", attached to the human body. Nowadays, accelerometer sensors are becoming part of the smart phones. They are used for aligning the display of the phone depending upon the direction in which phone is held. The presence of an accelerometer in a phone establishes a perfect situation where cell phone based accelerometer can be used as a part of an alternative authentication system.

1.2 Motivation

Daily, we pass through some kind of authentication mechanisms. For example, we must know a password to get access to the computer. We must enter a PIN in order to withdraw money from ATMs. Every authentication system has its own advantages and disadvantages. For instance, users are required to remember their passwords or PIN, users must use clean fingers for fingerprint authentication systems, and appropriate light must be present for face recognition system.

In recent days, human life is highly influenced by mobile devices. For instance, mobile phones are used for communication, mobile advertisements, mobile banking and mobile payments, etc. According to The International Telecom Union (ITU) [30] there are 5.3 mobile subscriptions in this world with a total population of seven billion. By the end of year 2015, 1 billion people of this world will be using mobile phone to access financial services. 250 million Facebook users actively use their mobile phones to access Facebook services. These developments also have significant downsize as mobile phone theft has been a big trouble for many countries. According to Citizens-Police Liaison Committee (CPLC) Pakistan [13] 82,000 cell phones are reported stolen, by Pakistani citizens every year. In 2005-06 around 80,000 mobile phones were reported stolen in UK [60]. As we know, all mobile phones come with the optional password based authentication system. This password based authentication systems reduces the usability of mobile phones and mobile phone users are not willing to use this authentication system. According to a survey [10] 13% of 548 participants were actually protecting their mobile phones by using passwords. In 86% cases users are not protecting their cell phones. Therefore, it is obvious that most of the cell phones which are reported missing are without password protection. This makes it quite easy for the stealer to get access to the private information of the mobile phone owner. To overcome this situation, there is a strong need of such authentication systems, which are unobtrusive, usable and robust. Unobtrusive nature of the authentication system will support periodic verification, which will ensure that phone is working under authorized user. In these situations, gait recognition meets most of the user requirements and in same survey 54% of users favored to use the biometric authentication system if added to the mobile devices. So, security of cell phones will significantly enhance by using human gait as alternative authentication mechanism.

1.3 Research Question

Previous researches [33], [23] showed that human gait is highly effected by different factors such as speed, shoes, clothes, aging, injuries, etc. However, in these studies dedicated wearable sensor was used to collect gait data. This study uses the data collected by mobile phone based accelerometer, which allows cost effective alternate solution for mobile authentication.

- The main research question of this thesis is to find the influence of different walking speeds (normal, slow and fast) and surfaces (flat carpeted, grass, gravel, and inclined) on cell phone's accelerometer sensor based gait recognition.
- In this project, we will also find the best parameter settings of different methods, used for analyzing the recorded data.

1.4 Scope

The ultimate goal of this thesis is come up with an answer how different walking speeds and surfaces influence gait recognition. In case, different speeds and surfaces do not influence the results too much then it would be quite easy that biometric templates extracted from the indoor walk can also be used to authenticate people if they are walking at different speeds or on different surfaces. In other words, once the enrollment is done then authentication can be moved to any other circumstance and there will be no requirement of enrolling the same person under different circumstances.

1.5 Target Audience

Biometric gait recognition is a recent topic for discussion. Therefore, it is not as effective as other biometric techniques such as fingerprints, face, iris or hand geometry. Target audience of this report includes the researchers, students and information security professionals working in the field of IT security and biometrics. As no one is untouched by the authentication mechanism in this era of technology so this report also targets all those who are concerned about personal data security.

1.6 Limitations

Gait-related data used in this thesis is recorded using the commercially available smartphone. This phone has an accelerometer sensor built-in. This sensor is limited to record data at the sampling rate of ∼40HZ, which is almost half of the dedicated sensor used for this purpose. This sensor has its own limitations such as it only output data when it detects some change in acceleration and in a steady state, vertical acceleration is exactly not equal to gravity and also time variant.

There is no availability of gait-related data sets as we have for fingerprints. Therefore, it is quite difficult to test algorithms on large data sets.Most of the previous studies do not discuss cross-day performance. Therefore, it is difficult to compare results of this study with other studies done in this area. Furthermore, methods, techniques, types of sensors and differs from study to study, which limits the comparison of this study to other studies.

1.7 Thesis Structure

This thesis consists of seven chapters. Next chapter describes the research methodology adapted for this scientific research. Chapter 3 consists of two main sections. First section explains authentication and its types. Second section gives a brief overview of biometrics, generic elements of a biometric system and different metrics to measure the performance of a biometric system. Chapter 4 reviews the research conducted in the area of biometric gait recognition with a focus on the wearable sensor category, as in this thesis cell phone based accelerometer is used for biometric gait data recordings. The complete process of biometric gait data collection is explained in chapter 5. Later in same chapter, the process of walk extraction and extraction of reference and probe cycles is explained. Chapter 6 presents methods used to analyze the data and best results of different walk settings. Conclusion and future work are given in chapter 7.

Chapter 2

Research Methodology

Two scientific research approaches *deductive* and *inductive* are considered for this research work. *Deductive* approach deduces hypothesis/es and objectiv/es from the lot of the information gathered by a researcher, e.g. theories, laws and principles. This approach demands numerical data, which can be gathered from empirical observations. Later, a researcher applies statistical analysis in order to evaluate his hypothesis and objectives. If his hypothesis is proven true, then the idea behind this hypothesis is also considered true. On the other hand, *inductive* approach is an opposite to the *inductive* approach. Here, inductive reasoning, observations and thoughts are transformed into the general theory.

This thesis is based on the philosophy of positivism as we work with observable reality, results can be generalized and there is a little personal interpretation of data. Since, this research is aimed to find out the influence of different walking surfaces and speeds on accelerometer-based biometric gait recognition. Earlier theories showed the influence of different factors such as shoe type, injuries, aging, carrying weights, etc. on gait recognition. This aim can be achieved if we measure the performance of accelerometer-based gait recognition on difference walking surfaces and speeds. Performance of different biometric technologies is measured empirically. Therefore, author has used deductive approach in this study.

Different studies have shown the influence of different factors on gait recognition by utilizing different types of sensors and techniques. Based on these theories, we have created our own hypothesis *"different walking surfaces and speeds will effect accelerometer based biometric gait recognition"* for cell phone-based

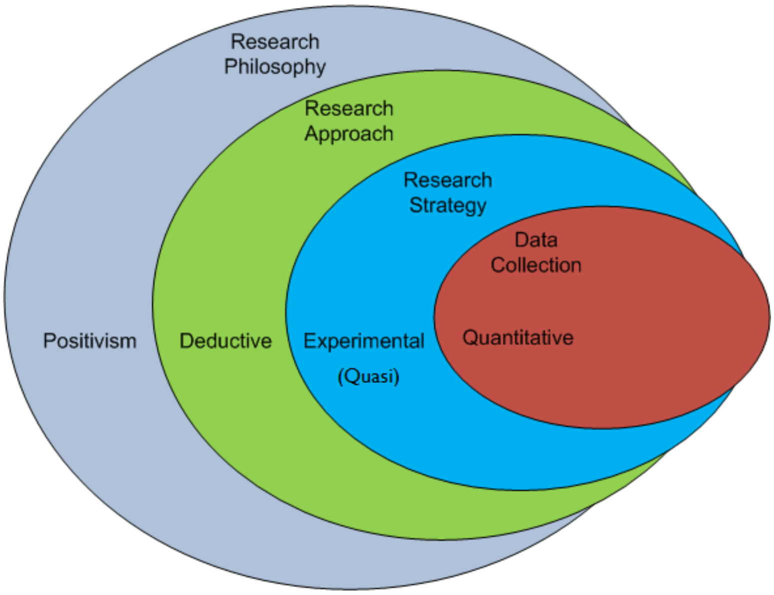

Figure 2.1: Methodology of our research

accelerometer gait recognition. Moreover, we narrowed down our hypothesis to develop our research questions.

We started with literature study to get better understanding of previous work generally in the field of biometric gait recognition and specifically about accelerometer based gait recognition. An extensive previous work on the accelerometer based gait recognition is given in literature review.

Data collected for this thesis is of quantitative nature as here we are recording the acceleration values measured by the accelerometer sensor of an android platform based cell phone. Our data collection strategy is of experimental nature and to be more specific it is *quasi experimental*. *Quasi experimental* is same as true experimental design except that quasi-experimental design does not include randomization process, which is the true characteristic of a classical experimental design. Since in this data collection process we neither created different groups of participants, nor we performed random allocation of participants to different groups therefore, our strategy to collect gait related data is *quasi experimental*. Detail of the entire data collection process is given in chapter 5.

During the literature review, we found that there are various ways for analysis of data recorded using accelerometer based gait recognition. After careful assessment, we used the methods suitable for our study and these methods processed the data in the quantitative manner. We have conducted various evaluations to answer research questions raised in this study. Quantitative assessment based on the results form these methods, helped us to determine the best settings for our experiments. In the end, a quantitative comparison of this study with other studies is presented.

Chapter 3

Authentication and Biometrics

This chapter provides a brief introduction of authentication and biometrics. In order to understand terms used in later chapters, it is important to be familiar with the terms and explanations introduced in this chapter. The chapter starts in section 3.1 with discussion of the basic means of identification and verification and section 3.2 provides background about biometrics.

3.1 Authentication

Authentication is considered as the front line of defence of every secure system. Authentication is a technical mechanism that prevents unauthorized people and processes from entering a system.

There are three methods [32], [77], [33] of authenticating a user, which can be used alone or in combination.

1. Knowledge-based (a secret e.g. password, Personal Identification Number (PIN) or cryptographic key)

2. Token-based (e.g. smart card or a door key)

3. Biometrics (e.g. such characteristics as a voice pattern, fingerprint, facial expression, hand geometry, iris and gait)

Apparently, any of these authentication methods could provide an adequate level of security. But there are different kinds of problems associated with each.

In order to circumvent an authentication mechanism, an unauthorized user must pretend to be a legitimate user. For this purpose, the unauthorized user can guess or learn the legitimate user's password or gait; they can also steal or fabricate tokens depending upon the used authentication mechanism. Following are the three modes of authentication.

3.1.1 Knowledge-Based Authentication

The most common and widely accepted form of authentication is based solely on something the user knows. In this authentication mechanism, the user-ID is coupled with a password [1]. Today, password-based authentication is used in all operating systems to prevent unauthorized users/processes to access different resources. In general, knowledge-based systems require the user to enter user-ID and password. When a user enters his[1] user-ID and password then the system compares the entered password with the previously stored password of this user-ID. In case of a successful match the user gets authenticated and is granted access to the system. It is a simple and cost effective mechanism to implement authentication in any environment.

There are many constraints that effect the security provided by the knowledge-based authentication mechanisms, such as users have to memorize different passwords and PIN for various applications. This encourages users to use the same password for different applications and to choose easy to remember passwords such as birthdays, family names, etc. In order to use different and random looking passwords users usually write down their passwords. As we know that, the security of password-based authentication systems mainly depends upon keeping the passwords secret. This in result leads the attacker to divulge the secret by using different techniques.

3.1.2 Token-Based Authentication

In this technique, the user possesses a piece of hardware. This piece of hardware is associated to the user's identity. There are authentication mechanisms, which

[1] Where he/his is used in this report you can also read she/her.

solely depend upon the something that an individual possesses. In some cases, PIN-based authentication is used with the hardware-based authentication This approach provides better security as compared to the single PIN/password based or hardware-based authentication mechanism. The piece of hardware that a user possesses and uses for the authentication purpose is called *token*. Tokens are generally divided in two categories [1]: *memory tokens* and *smart tokens*. *A memory token* stores user information but does not process this information, e.g. magnetic stripe cards. Special types of readers and writers are used to read and write information. *Smart tokens* not only store information but also process this information. Typical smart tokens require the users to provide a PIN in order to get authenticated to the system. Smart tokens can be divided into different types based on their physical characteristics, types of protocols they use and types of interfaces they use to interact with the card. This authentication mechanism is expensive in implementation and requires a special type of readers available at the time of authentication. In case of a lost or stolen token, the user will not be able to log in the system until he is provided with replacement, which in result requires strong administration.

3.1.3 Biometric Authentication

This authentication mode utilizes unique biometric (*physiological* or *behavioral*) characteristics of an individual in order to verify a person's identity. Biometric based authentication differs from the knowledge-based or token-based authentication in such a way that it requires the physical presence of the legitimate user at the time of authentication, whereas knowledge-based or token-based authentication mechanisms require the presence of secret or token, respectively. Biometric systems receive data directly from the user. This property of biometrics makes it difficult for attackers to forge or steal the biometric characteristics. Due to these reasons, biometric systems are being widely deployed in government (e.g. US-VISIT [74], Altinn [4], [57]) and commercial (e.g. Airports [31], Disney World [10]) sector.

3.2 Biometrics

The word "biometrics" is driven from two Greek words 'bios' and 'metric', which means life and measurement respectively [7]. This directly translates to life measurement. As we know, there are many biological measurements that can be used for authentication purposes. To qualify to be a practical biometric system, biological measurements must possess the following characteristics [33], [39]:

i) *universality*, which means every individual must have the characteristic.

ii) *distinctiveness*, which indicates no two individual should be same in terms of the characteristic.

iii) *permanence*, which means that characteristics should be invariant over time.

iv) *collectability*, which refers to quantitative collection of characteristics.

In order to distinguish individuals, these four characteristics are most important but practically three other characteristics are also used [39]:

v) *performance*, which refers to the achievable recognition accuracy, the resources required to achieve recognition accuracy, and the operational or environmental factors that effect the recognition accuracy

vi) *acceptability*, which indicates to what extent people are willing to accept the biometric system.

vii) *circumvention*, which refers to how easily the system can be fooled by using fraudulent techniques.

A biometric system can only said to be practical if it provides adequate accuracy, speed, is harmless to the user, widely accepted and robust against fraudulent technologies. Biometric systems can be classified into two groups and this grouping is based upon human biometric characteristics: *physiological & behavioral. Physiological* biometric characteristics can not be changed easily as these characteristics are derived from stable body parts e.g., fingerprints, hand geometry, iris and face. *Behavioral* biometric characteristics can be altered or learned e.g. keystroke, signatures and gait.

As we know, currently different biometric technologies are under investigation e.g. fingerprints, gait, voice, ear, hand geometry etc. It is difficult to say which technology is better than the other because each technology has its own advantages and disadvantages. Therefore, situation and demand can only determine the best biometric technology.

3.2.1 Generic Elements of Biometric Systems

All biometric technologies share common elements in *conceptual* and *functional* sense, refer to figure 3.1 for the pictorial presentation of conceptual and functional elements of a typical biometric system.

3.2.1.1 Conceptual Components of Biometric Systems

Conceptually, a typical biometric system consists of five subsystems [38]:

i) *Data capturing and transmission subsystem*, consists of a sensor module which captures biometric sample, e.g. image, signal from the subjects biometric characteristics and transmission module, which transmits samples to other subsystems for further processing.

ii) *Signal processing subsystem*, which consist of three modules a) *enhancement module*, which improves the quality of captured sample, b) *feature extractor*, which is responsible for extracting repeatable and unique measures from the captured sample and c) *quality checker*, which checks the quality of samples, features and references.

iii) *Data storage subsystem* is responsible for storing the data in the enrollment database. Some other subject-related information is also stored at the time of enrollment e.g. user identifier.

iv) *Comparison subsystem* is responsible for calculating the comparison score when one or more reference samples are compared against the probe samples and pass these comparison scores to the decision making subsystem.

v) *Decision making subsystem* provides the outcome based upon the comparison scores.

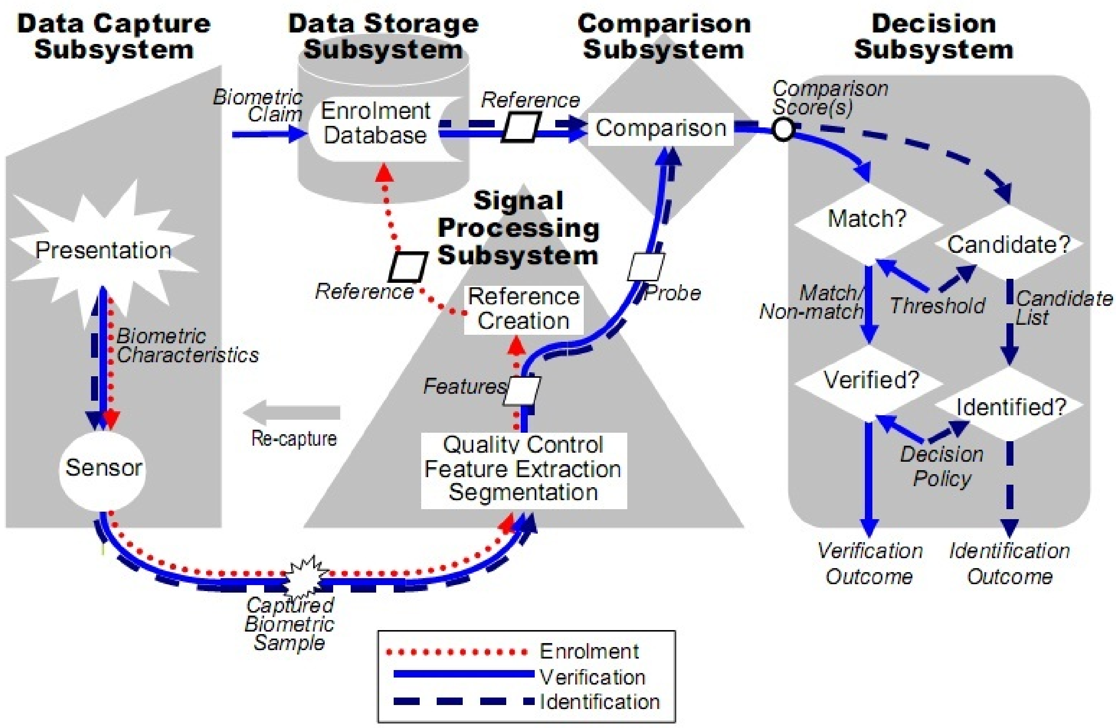

Figure 3.1: Generic components of biometric system[38]

3.2.1.2 Functional Elements of Biometric Systems

Following are the three functional processes of a generic biometric system [38]:

i) *Enrolment* process extracts biometric features of an individual from his biometric sample and these extracted features are stored as reference in the enrolment database. Enrolment process performs [38] acquisition of sample, enhancement of sample, feature extraction, quality check, reference creation and storage of extracted features.

ii) *Identification* process establishes the recognition of an individual's identity by a one to N comparison. The comparisons are performed between features extracted from the biometric samples (probe) and features of the biometric reference database. The feature of reference database which has best comparison score, is assumed to identify. Identification typically involves [38], acquisition of sample, enhancement of sample, feature extraction, qual-

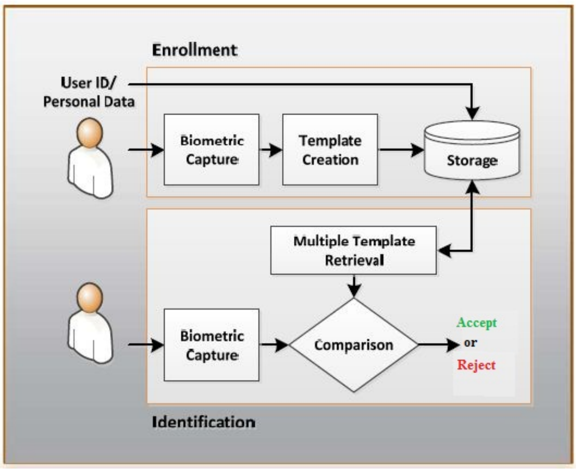

Figure 3.2: Graphical presentation of identification process

ity check, probe creation, comparison and decision making. Figure 3.2 is pictorial presentation of identification process

iii) *Verification* process utilizes user's identifier to establish his identity. The biometric system uses this identifier to the find feature of the individual in the reference database.

To verify the claimed identity, biometric system extracts features from the

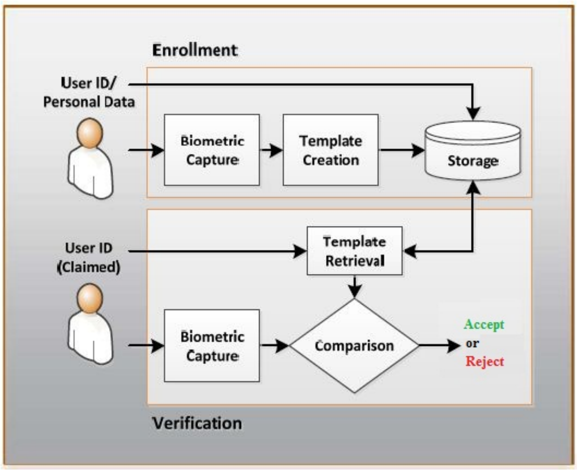

Figure 3.3: Graphical presentation of verification process

submitted biometric sample and compares them with the features identified by that individual's identifier. Verification process performs a one to one comparison and it is much faster than identification process. Verification involves same steps as identification refer figure 3.3 for graphical presentation of verification process.

3.2.2 Biometrics Performance Measures

ISO/IEC[1] has put forward the standardization process in the field of biometrics. ISO/IEC 19795 [36] standard establishes basic principles for testing biometric performance metrics in terms of equal error rates. It includes prediction and comparison of performance and specifies various performance metrics for better benchmarking different biometric technologies. This section explains the performance metrics which are relevant to this report. Mathematical formulas of these metrics are given in appendix B.

In knowledge-based or possession-based authentication systems, the user has guarantee of acceptance if he knows the correct password or has the correct token, respectively. In contrast, biometric systems do not ensure 100% acceptance rate because features can never match up to 100%. For the same user, we can find features that match with his reference template and that do not match with his reference template. There are two common ways to compare a biometric sample to a stored template.

i) *Distance metric*, where low value means less "distance," which indicates high correctness. Therefore, we want the low intra-class (comparing samples of the same person) distance metric and high inter-class (comparing samples of different persons) distance metric. ii) *Similarity score*, where high values indicate high level of correctness. Following error statistics are commonly used to study the performance of a biometric system [36]:

1. *False Match Rate* (FMR):

$$FMR(t) = \frac{Number of False Matches(t)}{Number of Imposter Attempts} \tag{3.1}$$

[1] International Organization for Standardization (ISO), International Electrotechnical Commission (IEC)

Where 't' stands for threshold.

2. *False Non-Match Rate* (FNMR):

$$FNMR(t) = \frac{NumberofFalseNon - Matches(t)}{NumberofGenuineAttempts} \tag{3.2}$$

3. *Failure to Acquire Rate* (FTA): occurs when a biometric system [36], i) fails to capture a biometric sample, ii) fails to extract features from the captured biometric sample or when iii) the extracted features are of insufficient quality.

4. *False Rejection Rate* (FRR): False reject occurs when the system incorrectly rejects the genuine subject. The frequency with which false rejects occur is called *False Rejection Rate*.

5. *False Acceptance Rate* (FAR): False acceptance occur when the system incorrectly authenticates an imposter. The frequency with which false accepts occur is called *False Acceptance Rate*.

FMR and FNMR are being used for studying algorithmic level authentication errors, whereas FAR and FRR are being used for studying authentication errors of whole biometric system. For calculating FAR and FRR, FTA is also considered. An ideal biometric system will have both FAR and FRR values equal to zero. However, biometric systems are not perfect. When biometric features are compared against stored templates, each comparison is assigned a certain similarity score. Theoretically speaking, all genuine similarity scores must be higher than imposter similarity scores, but this assumption is not true. Sometimes, imposter similarity scores are higher than the genuine similarity scores. Therefore, to classify genuine and imposter we use a threshold value. This threshold value decides if a subject will be accepted or not. If we choose high threshold to achieve a high security level where imposters will not get through, then all those genuine similarity score lower than the threshold will be rejected by the system. On the other hand, if we set low threshold value then all the imposter similarity scores higher than the threshold value will be accepted. Setting high threshold will reduce usability and increase the security of the system, whereas a low threshold will increase usability and decrease the security of the system. Therefore, it must be determined which trade-offs are required to achieve the desired level of security.

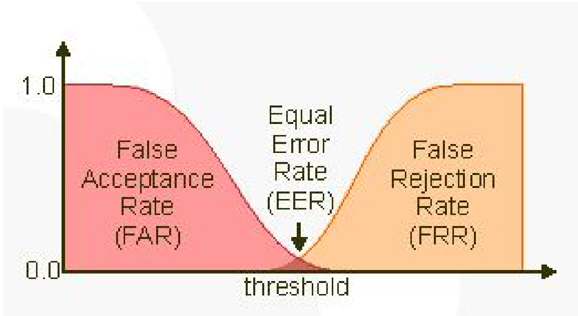

Figure 3.4: Threshold and similarity scores are on x-axis and recognition rate (%(FAR/FRR)) is on y-axis. With 0 threshold all imposter samples will be accepted. As the threshold increases, FAR will decrease, certainly a point will be reached, where no imposter sample will be accepted. At the same time, when increasing the threshold to make the system secure the FRR will also start to increase.[58]

The point where the FAR and FRR curves intersect is called Equal Error Rate (EER). EER is often used to measure the quality of biometric systems and lowest EER value is considered as the best [40]. Figure 3.4, shows FAR and FRR curves and EER point. The tradeoff between FMR and FNMR is also important

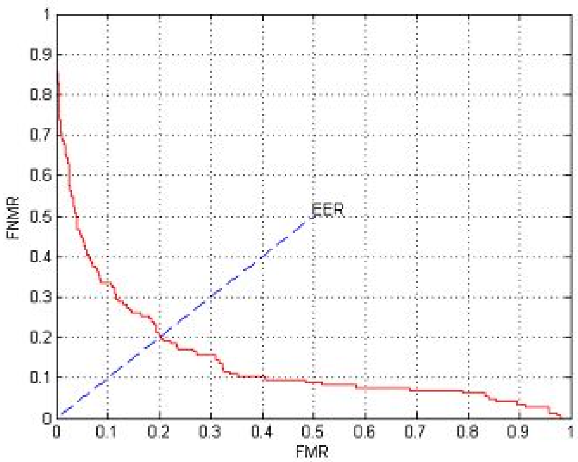

Figure 3.5: Decision Error Tradeoff (DET) Curve

because changing the threshold may give unequal changes in the two rates. Two commonly used tools are the Receiver Operating Characteristics (ROC) curve, and the Decision Error Tradeoff (DET) curve [33]. Only the DET curve will be used in this thesis, Figure 3.5 provides a conceptual illustration of DET curve. For every threshold value FMR and FNMR are calculated and then these points are plotted against each other. Reader should keep in mind that thresholds are very dependent on the system at hand, and these examples are only conceptual illustrations.

Chapter 4

Biometric Gait Recognition

Gait is an individual's style of walking [85]. Any intentional movement, which is associated with the human body such as walking, is regulated by a very complex process involving the nervous and musculo-skeleton system such as brain, spinal cord, peripheral nerves, muscles, bones and joints [90], [86]. Normal person's walk is cyclic in nature and one cycle is decomposed in two phases and each phase divided in several sub-events [90], as shown in figure 4.1. Distinctiveness

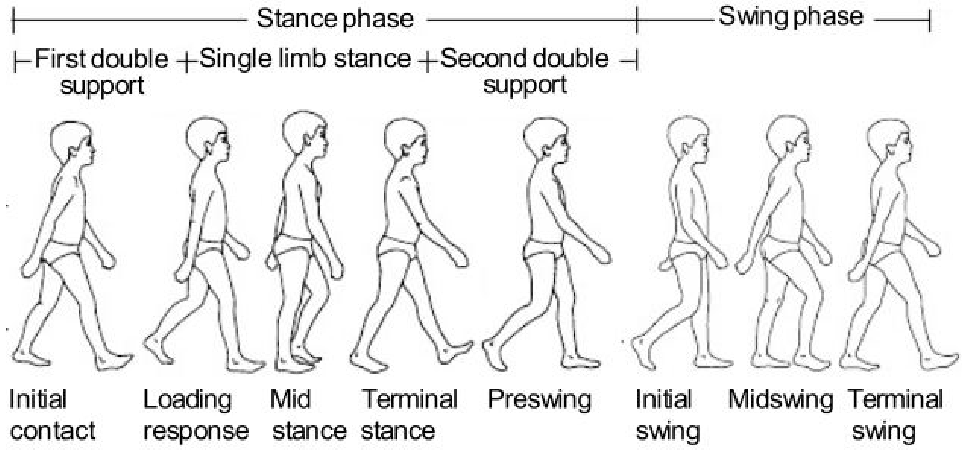

Figure 4.1: Gait of a child. In stance phase, one of the two feet is on the ground and during swing phase that same foot is no longer on the ground [86].

of gait patterns is indicated in early medical studies [63], [62]. Liu et al. [52] studied the role of each body part in successful recognition of a person. They showed that the recognition rate of experiments, which were just based on legs is equal to the ones based on the whole body silhouette and further said that head and torso shape have significant recognition power [52]. Some studies [50], [49], [26] indicated that foots also have discriminative power, which can be used for human recognition. Gafurov and Snekkenes studied [29] the discriminative power of foot ankle motion in relation to different shoe types. Biometric gait recognition is defined as using a person's distinctive style of walking for identification and verification [45]. Biometric gait technology is drawing lot of attention and recently it has become an active research area. Biometric gait technologies offer several advantages compared to the other biometric technologies such as,

i) *unconcealed*, i.e. difficult to hide and on other hand it is difficult to copy as brain reacts in against if one try to behave as another person. Gafurov [28], investigated spoof attacks and indicated that zero effort impersonation attacks on the gait do not significantly improve chances that an imposter will be accepted.

ii) *unobtrusiveness*, i.e. using machine vision gait technology, gait of a walking individual can be captured at a distance without his, a) knowledge that he is being analyzed, b) interaction with biometric sample acquisition sensor. In wearable sensor category subject has knowledge that his gait is being captured. However, subject needs not to interact with the acquisition sensor.

4.1 Approaches to Gait Recognition

Technically speaking following three approaches in biometric gait recognition exist [23].

4.1.1 Machine Vision Based Approach

Idea of the Machine Vision (MV) based approach is to capture gait from a certain distance by using video cameras. By applying different image and video processing methods, gait-related data is extracted [23]. MV approach is under continuous investigation for the last sixteen years [69]. Niyoji and Adelson [69] used two dimensional video footage to draw lines equal to the walking person's height and these lines vary with each person's characteristics. By applying differ-

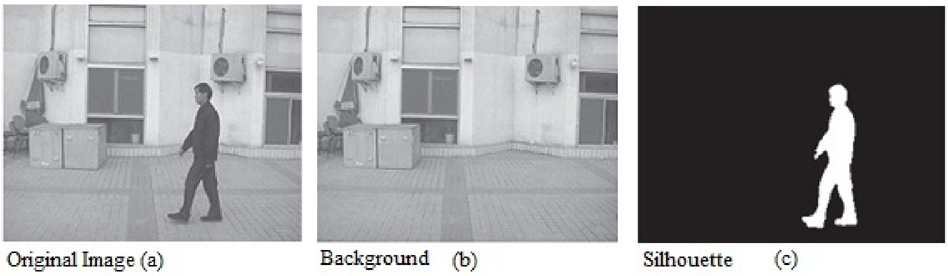

Figure 4.2: Extraction of human silhouette[88]

ent signal processing and gait recognition methods, they recognize 15 to 21 image sequences correctly out of 26. Further MV approach studies [14], [15], [17], [47], [51], [54], [88], [94] used single camera images to extract the human silhouette features, figure 4.2 explains silhouette extraction. In [96] multiple cameras were used to for constructing 3-dimensional human models and [92] used range-finders for 3-D model creation. Studies [15],[47],[88],[14],[96] used nearest neighbors and K-nearest neighbor classifiers, [94] used neural networks and [17] used support vector machines. Table 4.1 gives research conducted in MV-based approach.

Study	No. of persons	TRP%	Year
Yamanchi et al [92]	6	98.96-100	2009
Zhao et al. [96]	10	70	2006
Liu et al.[51]	14	92	2009
Yoo et.al [94]	30	83.3-90	2008
Dadashi et al. [17]	124	84.4-96	2010

Table 4.1: An overview of True Positive Rates (TPR) of current MV-based studies Reader should not consider this table as comparison of TPRs of different experiments, because each experiment is based on vital differences e.g. designs, cameras and walking speeds. This table is just to give an overview of recent work in MV-based approach.

One possible reason for great interest in MV-based research is the availability of large gait databases, such as Chinese Academy of Science database [23]. Because of unobtrusive nature, the MV-based approach is being used for surveillance and forensics [55], [46].

4.1.2 Floor Sensor Based Approach

The floor Sensor (FS) based approach utilizes sensors installed in the floor to collect gait data of an individual when he walks on it [48], [42], [70], [81]. Using the FS-based approach, one can easily collect gait features, such as ground reaction force (GRF) [70], pressure distribution of footsteps [43], heel-to-toe-time ratio [48] and heel length impact [81], which are difficult to collect with MV-based approach.

Study	No. of Persons	TRP%	Year
Nakajima et.al [64]	10	85	2000
Suutala and Röning [80]	10	65.8-70.2	2008
Sutala and Röning [81]	11	79.2-98.2	2004
Sutala and Röning [79]	11	92	2005
Middleton et al. [11]	15	80	2005
Orr and Abowd [70]	15	93	2000
Jenkins and Ellis [42]	62	39	2007

Table 4.2: An overview True Positive Rates (TPR) of current FS-based studies

The FS-based approach can be handy in situations like implementing access control to a building by placing mats with integrated sensors in front of office or building doors. These sensor mats can also be used to track a person's location inside the office [70]. FS-based approach is also being used by the physiologists to analyze patients of diabetic polyneuropathy [56]. Table 4.2 shows an overview of studies of FS-based approach in gait recognition.

4.1.3 Wearable Sensor based Approach

The Wearable sensor (WS) based approach is relatively new as compared to MV-based and FS-based approaches. First paper that indicated user authentication using WS-based approach was published in 2005 [2], [59]. Previously WS were used in medical research to analyze patients with locomotive disorder [23]. The WS-based approach utilizes motion recording sensors (MRS), (e.g. accelerometer sensors, gyro sensors or force sensor) which are attached to different parts of the human body (e.g. waist, pockets, shoes etc.) to record gait related data [2], [59],

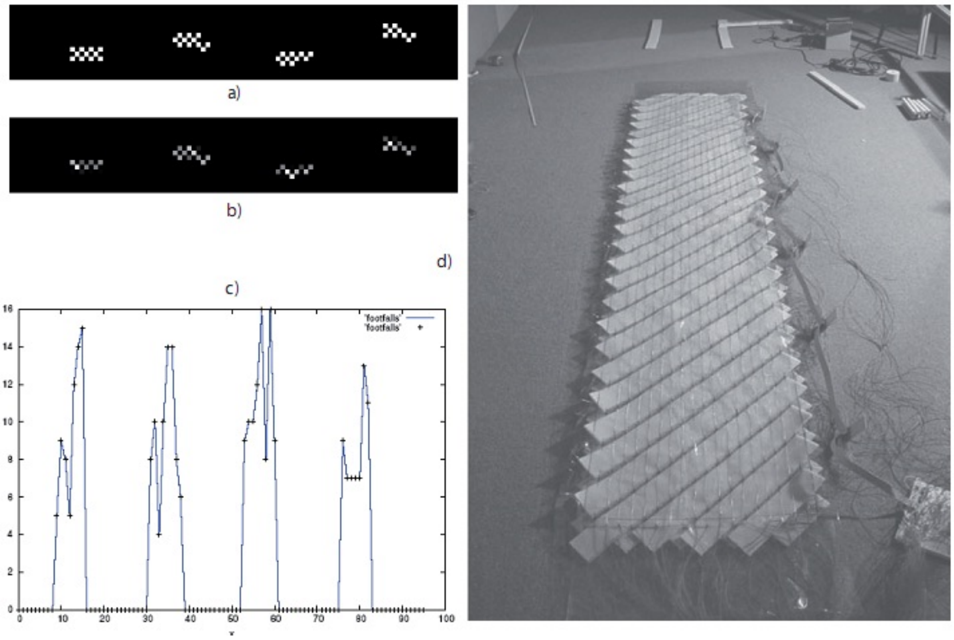

Figure 4.3: FS-based approach (a) detected footsteps, (b) time spent at each point, (c) heel to toe foot strikes and (d) mat with sensors installed in it. [33]

[61], [70], [71], [72], [87]. Later this recorded data is used for recognition purpose. In this thesis the accelerometer sensor, which is used for gait recognition, records data in three spatial dimensions: up-down, forward-backward and sideways direction [23]. Up-down and forward-backward accelerations were used in these studies [2], [59] [71], [72], [87]. Studies by Morris [61] and Huang et al. [35] are based on force, gyro and bend type sensors and they used identification mode for performance analysis. Table 4.3 on the following page, gives an overview of WS-based approach, indicated in various studies. All studies shown in table 4.3 used dedicated accelerometer sensors except Frank et al. [21], Kwapisz et al.[45] and Nickel et al.[19], [65], [66], [68], [67] used cell phone based accelerometer sensor.

Now a days, mobile devices are gaining more and more power. Smart phones and tablets are coming with accelerometer sensors. Ubiquitous nature of smart phones and presence of accelerometer sensors in these devices establishes a situation, which demands only development of new software. Smart phones use the built-in accelerometers to align the display depending upon the direction of

Year	Study	Sensor Type	Sensor Position	No. of Persons	Result metric (E,R,F)	Results
2005	Ailisto et. al [2]	dedicated	behind at the waist	36	EER	6.4
2006	Vildjiounaite et. al [87]	dedicated	hand	31	E	14.3-17.2
	Vildjiounaite et. al [87]	dedicated	hip pocket	31	E	14.1-16.8
	Vildjiounaite et. al [87]	dedicated	breast pocket	31	E	14.8-13.7
2007	Huang et al. [35]	Shoe Sensor	foot	9	R	96.93
	Rong et al. [72]	dedicated	back waist	21	E	5.6-21.1
	Rong et al. [71]	dedicated	back waist	35	E	6.7
	Gafurov et al. [23]	dedicated	trouser pocket	50	E	7.3
	Gafurov et al. [23]	dedicated	hip	100	E	13
	Gafurov et al. [23]	dedicated	arm	30	E	10
	Holien et al. [34]	dedicated	hip	25	E	12-18
2008	Holien [33]	dedicated	left leg (hip)	60	E	5.9-25.8
	Gafurov, Snekkenes [23]	dedicated	leg	30	E	5.60
2009	Gafurov, Snekkenes [23]	dedicated	leg/arm/waist	21 to 100	E	5-10
	Annadhorai et al. [5]	dedicated	leg	4	E	0
	Pan, Zhang, Wu [22]	Wii Remote	several	30	R	70
	Sprager [76]	phone	hip	6	R	93
	Bchlin et al. [6]	dedicated	leg	5	E	21.3
2010	Trivina et al. [3]	dedicated	back waist	11	E	3
	Gafurov, Hagen, Snekkenes [25]	dedicated	leg	10 (8complete)	R	59
	Gafurov, Snekkenes, Bours [23]	dedicated	leg	30	E	1.60
	Bours, Shrestha [8]	dedicated	left hip	60	E	1.60
	Wang, Li, Qiao [89]	dedicated	back waist	24	E	5
	Frank, Mannor, Precup [21]	phone	front pocket	25	E	0
	Kwapisz, Weiss, Moore [45]	phone	front pocket	36	E	0
	Derawi, Nickel, Bours, Busch [19]	phone	right hip	51	E	20
	Derawi, Bours, Holien [18]	dedicated	left hip	60	E	5.70
	Yan, Yue-e, Jian [93]	dedicated	waist next to the navel	10	E	6.29
	Gafurov, Bours [24]	dedicated	right hip	100	E	7.50
2011	Nickel et. al [67]	phone	right hip	48	E	10
	Nickel, Derawi, Bours, Busch [68]	phone	right hip	48	E	21
	Nickel, Brandt, Busch [65]	phone	right hip	48	F	0.39+0
	Nickel, Busch [66]	phone	right hip	48	E	6.15

Table 4.3: An overview of wearable sensor based studies, where E stands for EER, R for recognition rate and F for FMR+FNMR

phone is held (landscape or portrait), to show a photo in its proper aspect ratio, or control a game by the person's movements. Such devices can be used for gait recognition purposes with no additional hardware cost and customizations opposed to biometric-only sensors like fingerprint readers. The presence of accelerometers in lots of mobile devices makes WS-based approach really useful as an alternative user verification mechanism [9]. Some other studies [76], [84], [19] used cell phones for data collection and table 4.4, shows devices used in these studies.

4.2 Challenges in Gait Recognition

The University of South Florida [75] indicated some factors that may influence gait recognition. These factors include change in viewing angle, in shoe type,

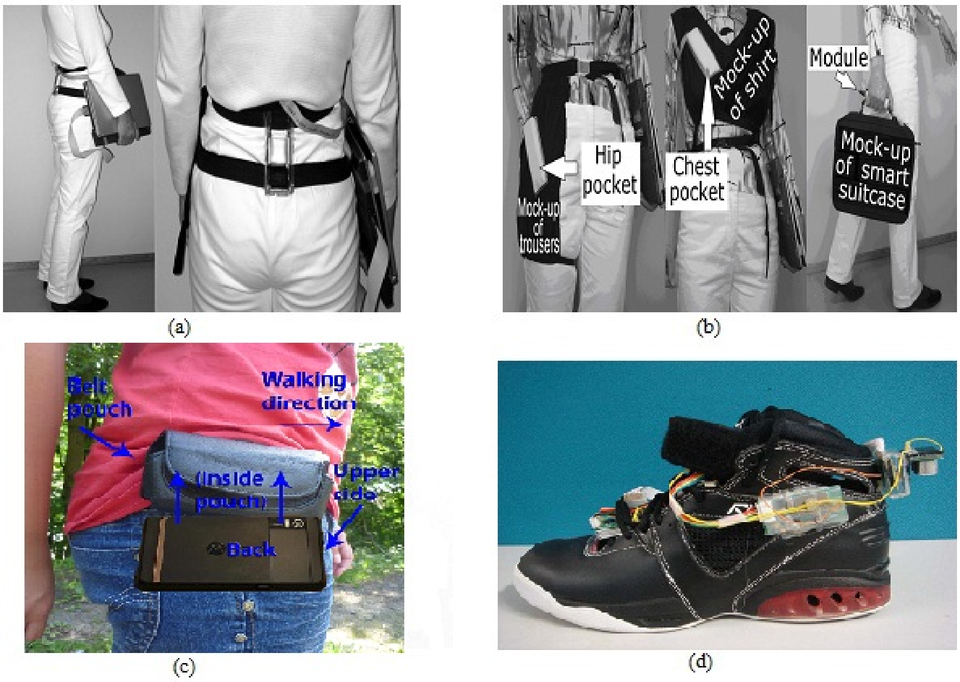

Figure 4.4: WS-based approach (a) [2] and (b)[87] different placements of dedicated accelerometer sensor on the body. (c) [9] cell phone with integrated accelerometer (d)[35] shoe with integrated sensors.

Study	Phone	Operating System	Sampling Frequency
Sprager et al.[76]	Nokia N95	Symbian S60	∼37Hz
Tanviruzaman et al.[84]	Apple	iPhone iOS	Unknown
Derawi et al. [19]	Google G1	Android	∼40Hz
Kwapisz et al.[45]	Several Phones	Android	∼20Hz
Nickel et al. [68]	Motorola Milestone	Android	∼125Hz

Table 4.4: An overview of devices used for gait data collection. [9]

in walking surface, carrying or not carrying a briefcase, and the elapsed time between samples being compared. In addition to that biometric gait technology is facing some more challenges [23] like aging, injuries, temporary health problems and clothing. FS-based and WS-based approaches are not effected by factors like lightening conditions and viewing angles. Daoliang et al. [82] studied the influence of lightning conditions, Yam et al. [91] studied the influence of running and Amit et al. [44] studied the influence of different viewing angles in MV-based approach of biometric gait authentication. Time influence, i.e. time elapsed between training and testing gait data collection, is also indicated in many studies in MV category [15], [54], [16], [53] but only in few WS-based [5], [6], [25], [66], [65] studies. Gafurov et al. in [25], indicated that time factor reduces the performance of gait recognition. Table 4.5 shows a comparison of same day and cross day recognition results.

Interestingly, some studies [33] reported that different walking surfaces, and speeds do not have significant effect on recognition rates. These studies were carried out under ideal conditions. Studies which were carried out under realistic scenario, e.g. [27] indicate that heavy foot wear reduces the discriminative power of foot.

4.3 Security in Gait Recognition

As we know, human gait is composed by behavioral characteristics, which make gait recognition systems vulnerable to impersonation attack. In impersonation

Study	Approach	Same day %	Cross day %	Time elapsed(days)	Year
Sarkar et al. [75]	MV	78	3	180	2005
Liu et al. [54]	MV	>80	0	180	2004
Liu et al [53]	MV	52-42	10-11	180	2004
Tanawonsuwan and Bobick [83]	MV	73	42	30	2001
Gafurov et al. [25]	WS	80-90	26-59	16	2010
Brandt [9]	Phone	0.39	25.6	2-3	2011
Nickel and Busch [66]	Phone	7.80	15.77	2-3	2011

Table 4.5: A comparison of same day and cross day recognition rates. [9]

attack, the attacker pretends to be a legitimate user to increase his chances of being accepted [23]. The security aspect (i.e. robustness against fraudulent techniques) of biometric gait, is yet not explored enough. Stang and Snekkenes [78] studied the security aspect of gait in WS-based category. Thirteen participants took a part in this experiment. For each participant, they created five gait templates (one normal and four abnormal templates). And every participant did 15 mimicry attempts. Results of [78] indicate that with training an attacker can improve his mimicry. Gafurov [28] studied security strength of gait in WS-based category. This experiment was conducted under two scenarios, i) *minimal effort attack* and ii) *closest person attack*. Results of this study indicate that biometric gait is robust against minimal effort impersonation attacks. However, attackers with knowledge of behavior of person being attacked can be a serious threat to the biometric gait system. A similar kind of study [58] indicates that gait mimicking is a hard task and difficult to learn as our physiology works against us when we try to follow one's style of walking.

4.3.1 Multi-modal Biometric Systems

Multi-modal biometric system technique is based on fusion of several biometric modalities for accurate identification and verification (e.g. fingerprints and gait [20]). This significantly improves the performance as compared to a single biometric system [73]. Studies [73], [97] indicate that multi-modal biometric systems are more robust against impersonation attacks, because it requires more effort to forge several modalities as compared to just one. Zhou et al. [97] conducted three experiments i) *face only*, ii) *gait only* and iii) *multi-modal (face and gait)* with a single camera for face and gait recognition. Recognition results of first two experiments *face only* and *gait only* was 64.3% and 85.7%, respectively. For the third experiment, they fused *face and gait* recognition and achieved a 100% recognition rate. Catting [12] showed in his studies when FS-based and MV-based biometrics are used in combined form the performance is significantly improved as compared to single MV-based or FS-based biometric system. Derawi [20], proposed a fused biometric (gait and fingerprints) system for authentication on mobile devices to improve the performance.

Chapter 5

Data Collection, Walk and Cycle Extraction

Previous chapters provided insight on authentication, biometrics and biometric gait recognition. This chapter will focus on gait data collection in context of this thesis. This chapter is composed of three main sections. Section 5.1 explains the process of gait sample collection. Section 5.2 will focus on extraction of relevant data from collected samples. The chapter ends with an analysis of the extracted data in section 5.3.

5.1 Data Collection

Biometric gait data used in this thesis is collected using the standard HTC Dream® (G1) smartphone. G1 is designed by HTC and uses Android as an operating system. Asahi Kasei Microsystems (AKM) has developed a package of (AK8976A) sensors that contains an accelerometer, a magnetometer, and a temperature sensor. All these sensors provide eight bit precision data. A chip containing this package of sensors is integrated in the G1. Accelerometer used in this phone is of piezoresistive type of MEMS (Micro-Electro-Mechanical-System). This accelerometer uses piezoresistors to measure the acceleration in three dimensions (x, y and z). Piezoresistors are made from piezoresistive material and they change their resistance under mechanical stress. Accelerometer sensor consists of a cantilever beam which tries to deflect from its neutral position when acceleration changes. This deflection acts as the mechanical stress which is measured by piezoresistors. See 5.1, for a schematic diagram of this principle.

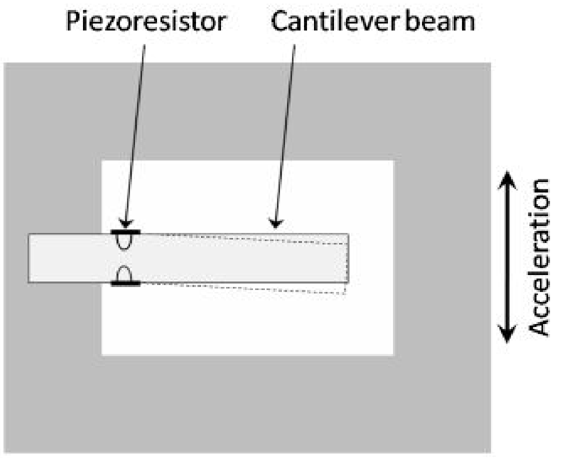

Figure 5.1: Schematic diagram of piezoresistor accelerometer [19]

Three accelerometers (perpendicular to each other) are used to measure acceleration in three directions. Using Android API (application program interface) a software was developed within CASED to access the sensor and write acceleration values (40-50 samples in three dimensions (x, y and z) with time stamps) in a text file stored on the SD-card.

5.1.1 Environment

In order to record gait data the phone was placed in a pouch attached to the subject's belt or trouser around his waist; on the right-hand side of his hip. Phone was positioned in such a way that its display points towards the body and earpiece points in walking direction, as shown in figure 5.2. Every participant was asked to walk on the following gait walk settings:

i) on a flat carpeted surface in normal, slow and fast pace

ii) on a grass in normal pace

iii) on a gravel surface in normal pace

Figure 5.2: (a) 3-axis in which acceleration is measured and (b) phone is attached to the subject.

iv) on an inclined surface in normal pace

Figure 5.4 shows the different walk surfaces used during this study.

Walking distance of each walk was around 37 meters and every participant was continuously monitored and advised to strictly follow data acquisition steps, given below:

- Pouch is attached to the subject's belt or trouser
- Subject goes to initial point
- Data recording program is started and phone is placed inside the pouch
- Subject starts walking towards stop mark (data collected during this walk belongs to fist walk)
- Subjects have to wait for 2 seconds
- Turn around and wait for 2 seconds and start walking towards the initial point (Data captured during this walk belongs to the second walk)

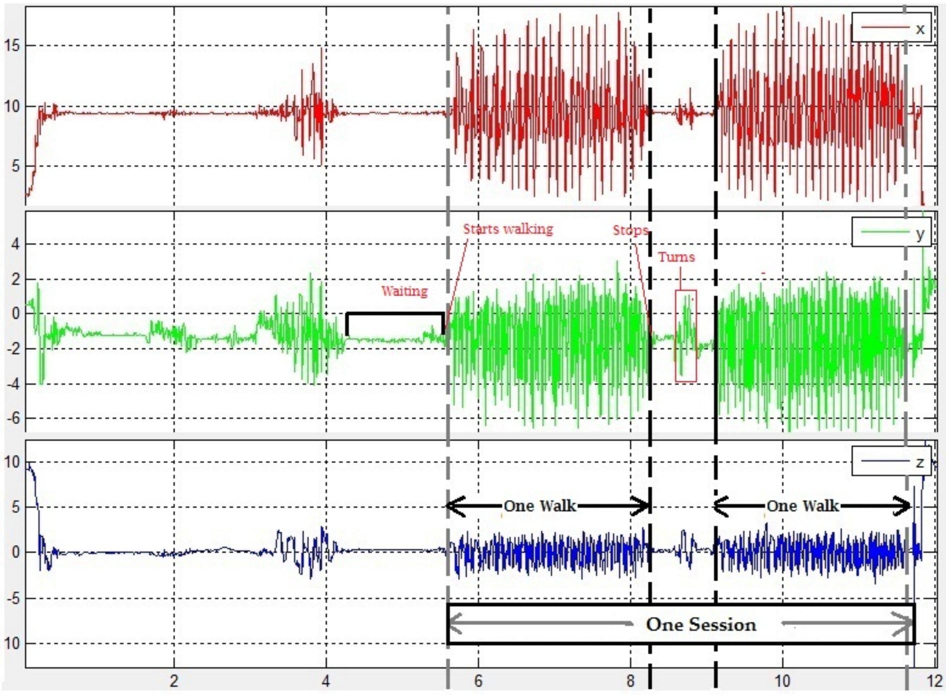

Figure 5.3: Acceleration data collected using G1

- Upon reaching initial point the walk process ends and phone is taken out of the pouch and the program is stopped

Figure 5.3 shows acceleration data (x-, y-, z-dimension) collected using the G1 in one session.[1]. As the gait of each person varies over the time and to enable a more realistic testing the gait data of all subjects was again captured on a different day. Most of the subjects were wearing same shoes for 2^{nd} day. For every subject four walks were recorded for each gait capture setting.

5.1.2 Volunteer Crew

A total of 48 volunteers participated in two gait data collection sessions. Every participant is assigned an ID and this ID is kept constant for all six walk settings. Refer figure 5.5 for age and gender distribution of participants.

[1]One session contains walking from point A to B and back to A.

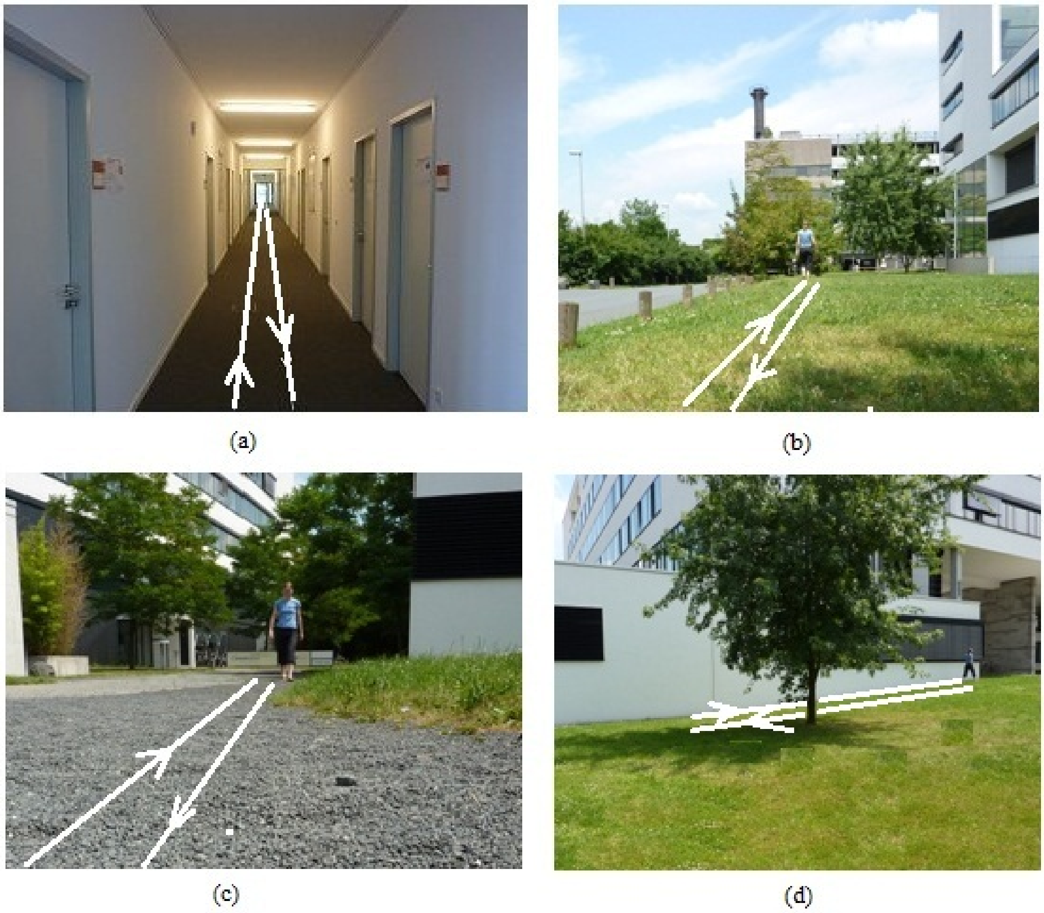

Figure 5.4: Walk settings (a) carpeted surface, (b) grass surface, (c) gravel surface and, (d) inclined surface

5.2 Walk Extraction

As we know by now, every session file contains two walks. In the next step from every subject's single session file, two walks are extracted in two sperate files. MATLAB™ GUI (Graphical User Interface) program "walk extraction GUI" developed in CASED, was used for this purpose. Walk extraction program automatically determines starting and ending points of a walk. Every walk is visually analyzed. In case automatic detection did not correctly extract the walk cycles, all unusual cycles before and after of each walk are omitted by manually setting starting and ending points of the respective walk. After separating one walk per file a total number of 192 walk files existed for each setting, which result from 48 subjects with two walk sessions. Walk extraction process is repeated for

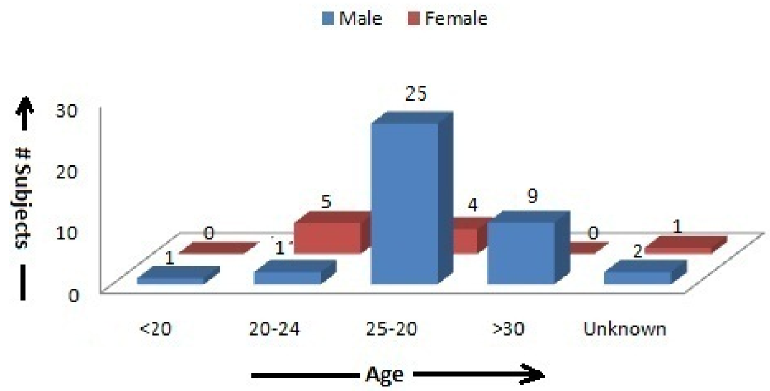

Figure 5.5: Volunteer Crew

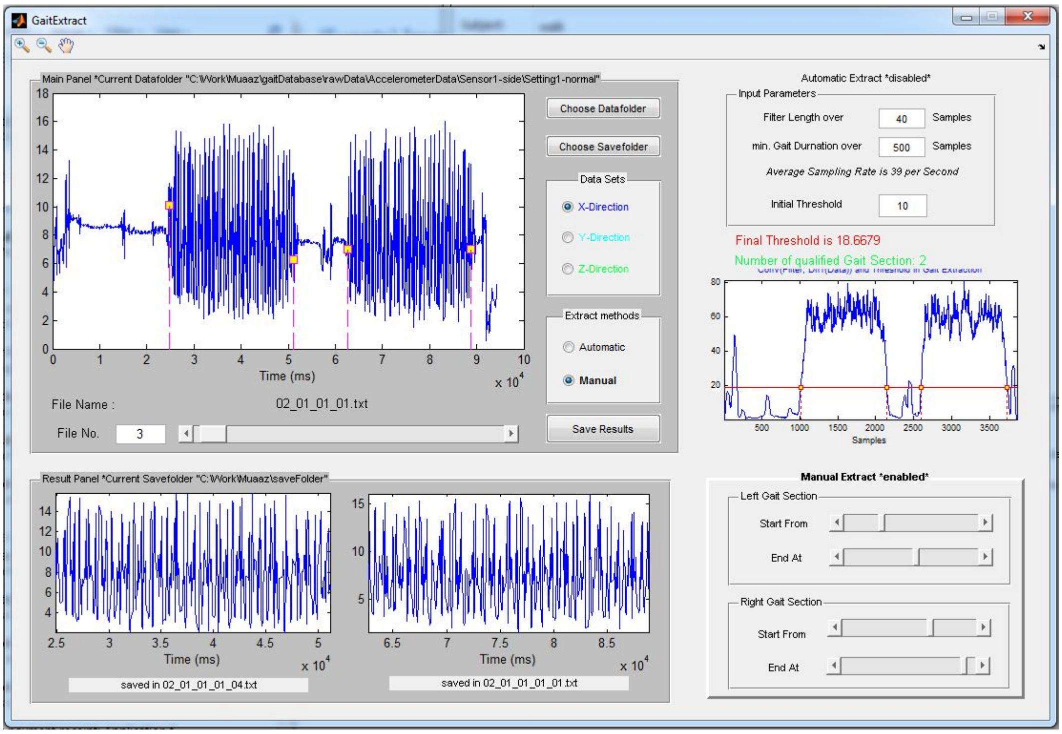

Figure 5.6: An overview of walk extraction GUI

all walk settings. In figure 5.6 an example of a walk extraction setting is given. The data from the original session file is visible in the upper large window and the two extracted walks below.

5.3 Sample Analysis

After separating each walk, there are various ways to analyze the walk/raw data recorded by the accelerometer. Following subsections will explain various methods and algorithms used in this thesis for extracting the cycles from the raw data. These cycles are used to determine best cycle for each subject. These methods for analysis are based on the work of [68]. As we know, the accelerometer used in this thesis reports data in 3 dimensions (x, y and z). But only acceleration measured in x-direction (vertical direction) is used for analysis as it has given the best results so far [19].

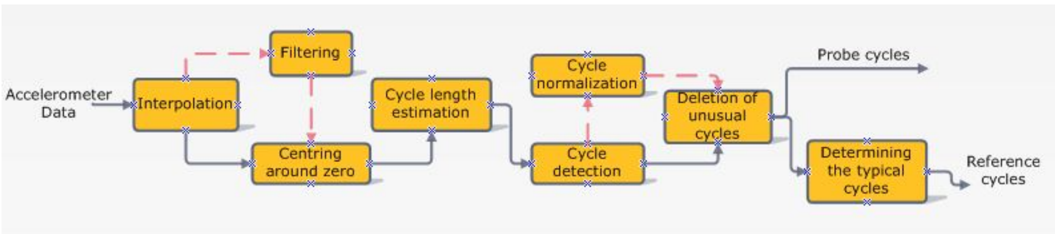

Figure 5.7: Cycle extraction steps

5.3.1 Interpolation

Due to limitation in Android API, the accelerometer sensor only outputs acceleration data whenever there is change in its values. Therefore, consecutive data values, sometimes do not have fixed time intervals. So, first step is to interpolate raw data because interpolation ensures that time intervals between two sample points are fixed. There are different variants of interpolation (e.g. linear, polynomial and spline) but linear interpolation is sufficient and used for this work.

5.3.2 Filtering

Weighted Moving Average (WMA) filter is used to reduce the noise. In WMA multiplying factors are used to calculate weights and these weights are assigned to acceleration data in different positions. In this thesis, WMA filter with sliding window of size five is used. Equation 5.1 shows the formula of WMA with window size of five where "a_t" is acceleration value at time t. Filtering is an optional step.

$$WMA(a_t) = \frac{(a_{t-2} * 1) + (a_{t-1} * 2) + (a_t * 3) + (a_{t+1} * 2) + (a_{t+2} * 1)}{9} \tag{5.1}$$

5.3.3 Centering around Zero

When subject is steady (no movement), acceleration measured by the G1's accelerometer is not equal to gravity (as we are using vertical acceleration here) and is also time variant. To overcome this situation zero normalization is applied. Zero normalization ensures that all elements of input acceleration vector are transformed into output acceleration vector whose mean is ∼0. Here it is done by subtracting mean acceleration μ_a from the acceleration in respective dimension a as shown in equation 5.2.

$$\bar{a}_t = a_t - \mu_a \quad where; a = x, y, z \tag{5.2}$$

5.3.4 Cycle Length Estimation

After preprocessing steps (interpolation, filtering and zero normalization) the cycle extraction process is applied. The first step is to estimate the cycle length. This step is done by computing the minimum salience and maximum salience vectors. In min-salience vector each data value is assigned a number. A data value is compared by its following data values and each comparison is counted till we find the first smaller value than that data value. This counter value is basically that number which is placed in salience vector in-place of that data value which is compared with its following data values. Similarly, max-salience vector is computed by using the maxima. Each value of salience vector is compared with min-peak-height and min-peak-distance values. These parameters are experimentally calculated to give best results.

$$min - peak - height = 0.8 * interpolation frequency \tag{5.3}$$

$$min - peak - distance = 0.5 * interpolation frequency \tag{5.4}$$

If a particular value of salience vector is greater than the min-peak-height value (called a peak) and has distance of at least min-peak-distance to the next peak then it is assumed to correspond to a cycle start. Standard deviation is used to determine if more regular spread peaks are from the the min-salience or max-salience vector. Average cycles length is based on the more regular spread peaks. If standard deviation of min-salience vector is less than standard deviation of max-salience vector, then distances (rounded mean values) of neighboring peaks of min-salience vector are used to computed average cycle length otherwise rounded mean distances of neighboring peaks of max-salience vector are used.

5.3.5 Cycle Detection

Cycle detection is also based on min-salience and max-salience vectors. In the salience vector the peaks with parameters like min height (0.7 * interpolation frequency) and distance at least half of estimated cycle length are computed. These peaks are used as initial cycle starts in case of min salience vector. However, the case of max salience vector is different. Here the minimum before the detected maximum is used. The number of unusual long cycles (with length greater than 1.5 times the estimated cycle length) is calculated to determine which one (minimum or maximum salience) is well suited for computing the cycle starts. The one which results in less ir-regular (unusual) cycles is supposed to be the best and its respective cycle starts are used. Once again min-salience and max-salience vectors are used to divide the too long cycles (determined previously). This process produces additional cycle starts, so both initially identified cycle starts and additional cycles starts produce the final set of cycle starts. Figure 5.8 shows an example of detected cycles

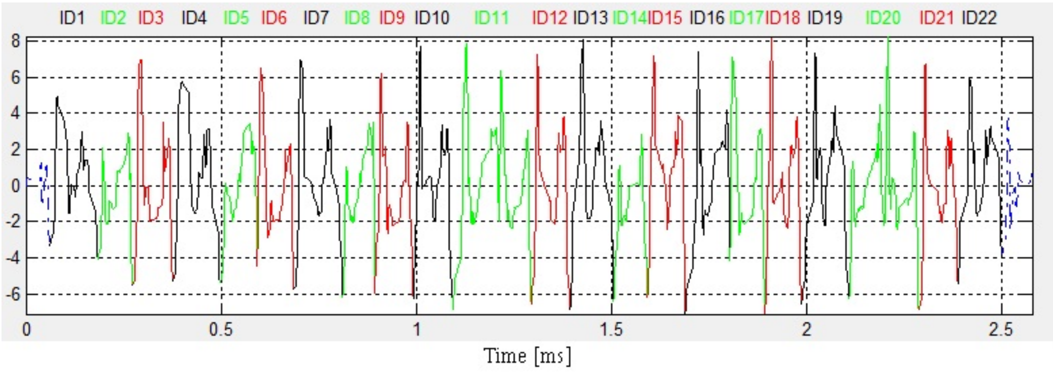

Figure 5.8: Detected cycles after applying cycle detection method

5.3.6 Cycle Normalization

Detected cycles are normalized to equal length using linear interpolation because some distance functions such as Euclidean distance require vectors of equal length as input. Normalization is an optional step.

5.3.7 Deletion of Unusual Cycles

All detected cycles are passed to a function which deletes unusual cycles. This function uses Dynamic Time Warping (DTW) (see section 5.3.7.1) scores to remove outliers from a set of cycles. Distances between all possible cycle pairs are computed. To decide which cycles must be omitted we set a threshold value. Cycles which have a distance of more than the threshold to at least half of the cycles are omitted. The cycle which has lowest distance to the remaining cycles is called the closest cycle. If less than three cycles remained then the threshold value is increased by 10 and the same process of deletion of unusual cycles starts again until at least three cycles remain. After deleting unusual cycles all cycles are called *remained cycles*.

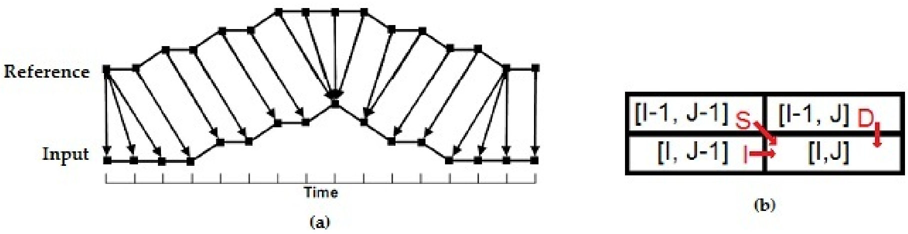

Figure 5.9: Dynamic time warping [33] (a) Two time sequences being mapped (b) Insertion(I), Deletion(D), Substitution(S)

5.3.7.1 Dynamic Time Warping (DTW)

Time warping distance is an effective measure to find similarity between a pair of time series sequences. Warping distance is normally evaluated by dynamic optimization therefore, it is called as Dynamic Time Warping (DTW). The warping distance between the two time series k and l is defined as the length of shortest warping path in a directed graph. In this graph each node represents the alignment of corresponding periods of two time series whose similarity we want to compute. All nodes can be connected on vertical, horizontal and diagonal axis. Transforming the sequences is supported by operations like *substitute, delete* and *insert* and each operation has some cost. DTW was first introduced for speech recognition. Speech recognition algorithms deal with string sequences but here in case of gait recognition, the algorithm deals with a sequence of numbers. While warping two sequences *insertion* takes place when many points of reference sequence match to the the single point of the input sequence. *Deletion* occurs when multiple points in the input sequence match to a single point in the reference sequence. *Substitution* occurs when a point in the reference sequence matches to the same point in input sequence.

We applied the classical DTW algorithm. We have two time sequences A and B with a length of n and m respectively, where: A $= a_0, a_1, a_2, a_3, ..., a_i, ..., a_n$ and B $= b_0, b_1, b_2, b_3, ..., b_j, ..., b_m$. To align two sequences a n-by-n matrix C is created by replicating A^T and m-by-m matrix D is created by replicating B. Now a matrix E of length n-by-m is created, where; $E(1,1) = (C(1,1) - D(1,1))^2$. Each value of matrix E can be achieved by using this simple equation.

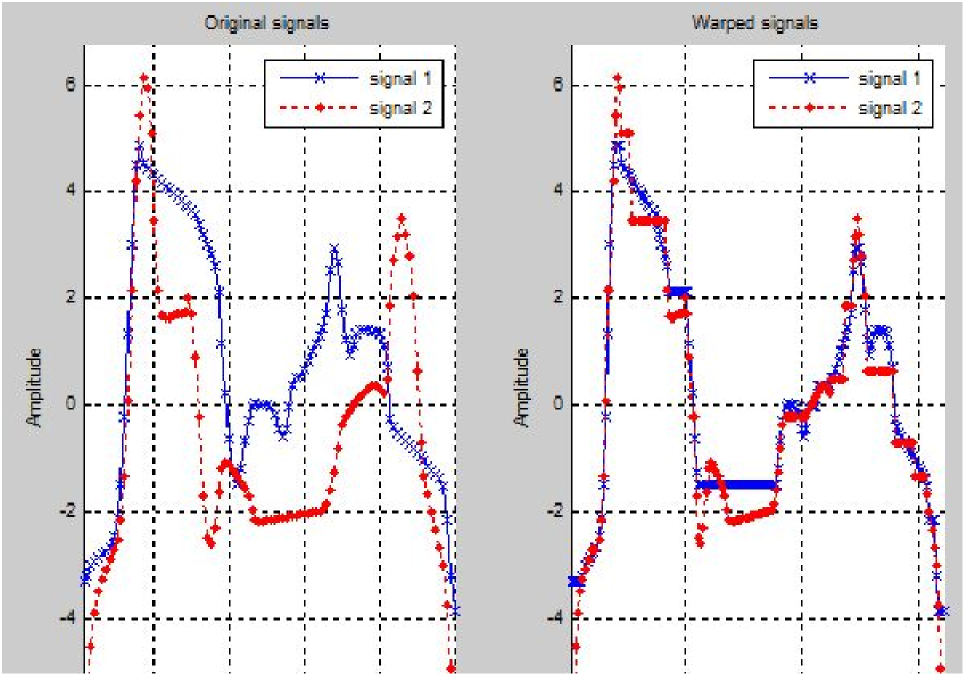

Figure 5.10: Comparison of original and warped cycles of gait signal

$$E_{ij} = (C_{ij} - D_{ij})^2; \forall \{i = 1...n, j = i...m\} \tag{5.5}$$

Then a matrix e is created, where; e(1,1)= E(1,1). In this matrix e first column contains the cost of deleting the value (calculated by e(n,1) = E(n,1) + e(n-1,1)) and first row contains cost of inserting the value (calculated by e(1,m) = e(1,m) + E(1,m-1). Then we carry on from left to right and from top to bottom with the rest of the grid e(n,m) = min(e(n-1,m1), e(n1,m), e(n,m-1)) + E(i, j). e(n,m) contains the DTW distance which is the cost of the shortest path. Figure 5.10 shows the difference between original and warped signals.

5.3.8 Computation of Typical Cycle

From remained cycles one cycle which has been determined to be the closest cycle in the previous section (5.3.7) is called typical cycle in case if samples are not normalized in (5.3.6). If normalization process (explained in subsection 5.3.6) is applied then mean or median of closest cycles can also be used as determine typical cycle. Figure shows 5.11 a typical cycle, this cycle is determined as a closest cycle.

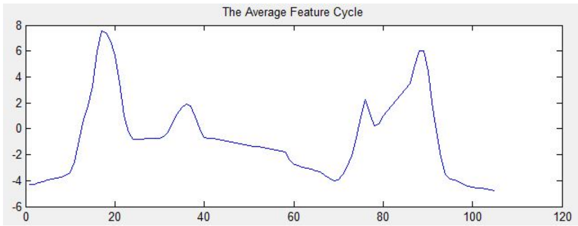

Figure 5.11: A typical cycle

After applying all methods described above, detected, featured, remained and normalized cycles are stored in separate directories.

Chapter 6

Evaluation, Analysis and Results

Section 6.1 explains the execution details of different experiments carried out to answer the questions placed in section 1.3. Analysis of the data produced after sample analysis (described in section 5.3) is given in section 6.2. Section 6.3 presents the results of the experiments.

6.1 Evaluation Details and Execution

To study the influence of different walking speeds and different undergrounds on the accelerometer-based gait recognition, two experiments were conducted for each walk setting. In experiment (A) *typical cycles are used as reference cycles and remained cycles are used as probe cycles* and in experiment (B) *remained cycles are used as both reference and probe cycles*. Experiment (A) contains 34 tests and experiment (B) contains 22 tests, respectively. Reason for conducting 34 tests in experiment (A) is to find the best setting which results in minimum EER value. Experiment (B) is just an extension of experiment (A) to study if increasing the number of reference cycles will improve the results or not. Experiment (B) is applied only on those tests which have low EER values (good results). However, the tests of both experiments are divided into two groups i) *normalized (when cycle lengths are normalized by using cycle length normalization method)* and ii) *not normalized (when cycle lengths are not normalized)*. Each test is different from the other, in sense of different settings of the parameters of methods.

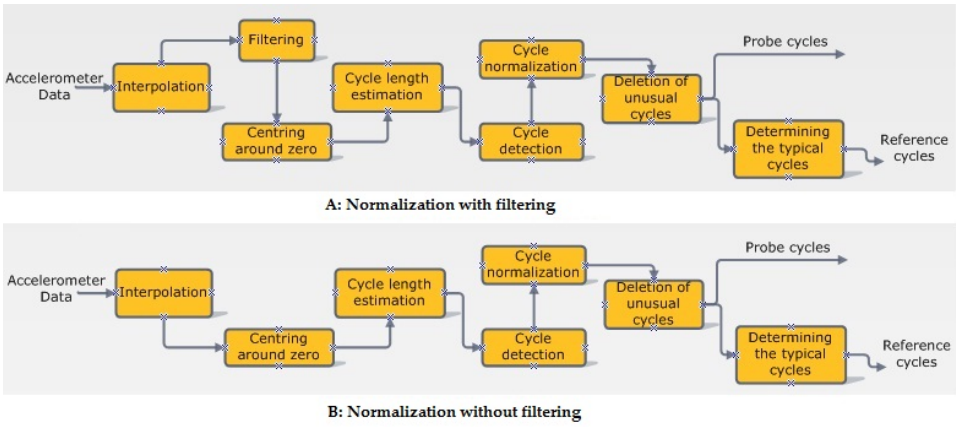

Figure 6.1: Flow control of sample analysis methods when normalization method is applied

These methods are explained in section 5.3. Explanation of these parameters is necessary because changing any parameter effects the final results of the tests. Details about parameters of different methods and their formulas are given in section A.1 of appendix A. Most of the test share the same number of methods. However, WMA filter and normalization methods are applied only in some tests. Table 6.1 on the next page shows different test settings used. Flow control of these tests is shown in figures 6.1 and 6.2. Figure 6.1 shows the flow control of tests when the normalization method is applied and 6.2 shows the flow control of tests when normalization method is not applied.

6.2 Analysis

Reference and probe cycles are compared against each other to compute intra class (genuine attempt) and inter class distances (imposter attempts). Suppose, we have 'P' subjects and 'Q' recordings per subject then number of genuine attempts can be calculated form P * (Q-1) whereas, imposter attempts can be calculated by P * (P-1)(Q-1). In addition to help us computing the typical cycles dynamic time warping (described in section 5.3.7.1) is used to compute the distances of reference cycles to all probe cycles. Advantage of using DTW is that reference cycles and probe cycles not have to be of same length. Distances

With Length Normalization Method					
	Preprocessing		Gait Feature Extraction		
tests	T-interpolation	Filter	L-normalize	C-deletion	Typical Cycle Best/Median
C1	Frequency = 100	No	Yes:100	Yes :50	Best
C2	Frequency = 80	No	Yes:100	Yes :50	Best
C3	Frequency = 60	No	Yes:100	Yes :50	Best
C4	Frequency = 50	No	Yes:100	Yes :50	Best
C5	Frequency = 40	No	Yes:100	Yes :50	Best
C6	Frequency = 30	No	Yes:100	Yes :50	Best
C7	Frequency = 100	No	Yes:100	Yes :50	Median
C8	Frequency = 80	No	Yes:100	Yes :50	Median
C9	Frequency = 60	No	Yes:100	Yes :50	Median
C10	Frequency = 50	No	Yes:100	Yes :50	Median
C11	Frequency = 40	No	Yes:100	Yes :50	Median
C12	Frequency = 30	No	Yes:100	Yes :50	Median
C13	Frequency = 100	No	Yes:120	Yes :50	Best
C14	Frequency = 100	No	Yes:80	Yes :50	Best
C15	Frequency = 100	No	Yes:40	Yes :50	Best
C16	Frequency = 50	No	Yes:120	Yes :50	Best
C17	Frequency = 50	No	Yes:80	Yes :50	Best
C18	Frequency = 50	No	Yes:40	Yes :50	Best
C19	Frequency = 100	No	Yes:100	Yes :80	Best
C20	Frequency = 100	No	Yes:100	Yes :30	Best
C21	Frequency = 50	No	Yes:100	Yes :80	Median
C22	Frequency = 50	No	Yes:100	Yes :30	Median
C23	Frequency = 100	yes	Yes:100	Yes :50	Median
C24	Frequency = 50	yes	Yes:100	Yes :50	Median
Without Length Normalization Method					
	Preprocessing		Gait Feature Extraction		
tests	T-interpolation	Filter	L-normalize	C-deletion	Typical Cycle Best/Median
C25	Frequency = 100	No	no	Yes :50	Best
C26	Frequency = 80	No	no	Yes :50	Best
C27	Frequency = 60	No	no	Yes :50	Best
C28	Frequency = 50	No	no	Yes :50	Best
C29	Frequency = 40	No	no	Yes :50	Best
C30	Frequency = 30	No	no	Yes :50	Best
C31	Frequency = 100	No	no	Yes :80	Best
C32	Frequency = 100	No	no	Yes :30	Best
C33	Frequency = 100	yes	no	Yes :50	Best
C34	Frequency = 50	yes	no	Yes :50	Best

Table 6.1: T-interpolation means time interpolation, filter stands for WMA filter, L-normalization stands for length normalization and C-deletion means deletion of unusual cycles

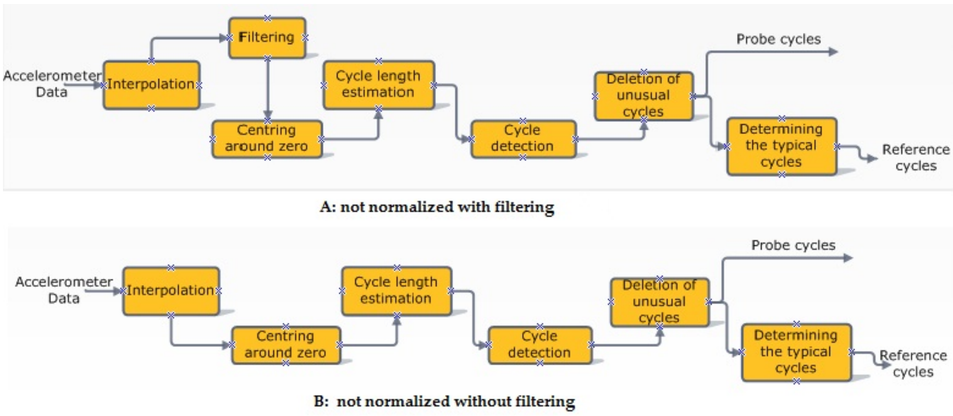

Figure 6.2: Flow control of sample analysis methods when normalization method is not applied

computed using DTW are then passed to another function called *majority voting*. This function uses a preset threshold value which determines a false match or a false non match. There are two types of distance metric i) intra class distance is obtained when two cycles from the same person have distance lower than the threshold and ii) inter class distance is used when two cycles from the different persons scores higher than the threshold value . For each cycle it is computed if there would be an acceptance based on it. If at least 50% of the cycles 'vote' for an accept, the result of the comparison is an accept. By dividing false match with the total number of imposter results, FMR is computed. Similarly, by dividing false non match with the total number of genuine results FNMR is computed. Then index wise comparison of both vectors (FMR and FNMR) is done to find a same value in both vectors. This value is called EER. In case if there is no equal value in both vectors, then average (of last small and first large value of FMR vector and last large and first small value of FNMR vector) is used to determine EER value. This function also provides DET curve. The error rates are computed separately for the different walks and joint error rates are also computed. Joint equal error rate is computed by index wise comparison of joint false match rates and false non match rates. Joint false match rate is achieved by dividing the sum of all false match rates i.e FM1, FM2 and FM3 with sum of the total number of imposter attempts. Similarly, joint false non match rate is calculated by dividing the sum of false non matches i.e FNMR1, FNMR2 and FNMR3 with the sum of the total number of genuine attempts.

6.3 Results

From last chapter we know that six different walk settings are used in this thesis. This section starts with the explanation of normal walk as results form normal walk will give us the opportunity to compare our results with previous studies given in chapter 3. In these experiments under a single test, four EER values are calculated (EER1, EER2, EER3 and joint EER). As we know, a user have four walks from two sessions. These walks are named as follows:

- W1S1: first walk of first session
- W2S1: second walk of first session
- W1S2: first walk of second session
- W2S2: second walk of second session

EER1 shows same day results as EER1 is result of when pairwise distance metrics of session one walks (i.e. W1S1 and W2S1) goes under majority voting. EER2 is computed when majority voting is applied on distances determined by the comparisons of W1S1 and W1S2. Similarly, EER3 is calculated by applying majority voting on distances calculated in result of comparison of S1W1 and W2S2. EER2 and EER3 are cross day results. Joint EER presents combined equal error rate of all three files.

6.3.1 Normal Walk on Carpeted Surface

After applying preprocessing steps on normal walk, cycle detection method detected 18 to 22 cycles per walk. Total number of genuine attempts are 48 * (4 - 1) = 144 and total number of imposter attempts are 48 * 47 * 3 = 6768. The results of both experiments, experiment A (typical cycles are used as reference cycle) and B (remained cycles are used as reference cycle) are shown in table A.1. All comparison tables shown in this subsection are extracted from table

A.1. In general, the results of experiment B are slightly better than the results of experiment A. From the results shown in table 6.2 it is clear that same day results are much better than cross day results i.e. EER1 results are better than EER2 and EER3. There was no big difference between session one and session two recordings except some subject changed their shoes. The factor of clothing is also very effective as cell phone was placed inside the pouch attached to the body. The height of the pouch varies from person to person. From table 6.3 tests (C23, C24, C33 and C34) when compared with (C1, C4, C25 and C28) show that WMA filter does not improve the results at all. If we compare results of tests (C1, C19 and C20) as shown in table 6.4 it is clear that setting a threshold of 50 for deleting unusual cycle seems ideal as we slightly increase or decrease the threshold value it increases the EER2. Comparison of results of C1 and C7 in table 6.5 shows that typical cycles based on closest cycles approach have better results as compare to the median cycles obtained from closest cycles. From the results one can not determine which interpolation frequency achieves best results as there is no fix trend. In both cases (*normalized & not normalized*) interpolation frequency of value 100 have given best results. However, the first six test results of *normalized* and of *not normalized* sections shows that there is a minute difference in results of these tests. The results from table A.1 which have minimum Joint EER values along with minimum same day and cross day results i.e. EER1, EER2 and EER3 are considered as best results. Three best results are shown in table 6.2.

Normal Walk Best Results								
	Normalized							
	Equal Error Rates - Experiment A				Equal Error Rates - Expermient B			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER
C13	0.1626	0.2939	0.2821	0.2534	0.1752	0.2696	0.2848	0.2481
C16	0.1648	0.2893	0.3105	0.2664	0.1694	0.2944	0.3287	0.267
	Not Normalized							
C25	0.1375	0.3053	0.3107	0.2621	0.1533	0.3111	0.3094	0.2654

Table 6.2: Normal walk best results (refer table 6.1 on page 45 for best settings)

6.3.2 Slow Walk on Carpeted Surface

In next circumstance, subjects were asked to walk slower than their normal speed. For this purpose the subject reduces his velocity and subject has to take more

Tests when WMA filter is not applied													
	Equal Error Rate-Expermient A				Equal Error Rate-Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER	T-Interpolation	Filter	C-normalize	C-deletion	T-cycle BestMedian
C1	0.1482	0.3285	0.3318	0.2792	0.1456	0.2922	0.3021	0.2503	F = 100	No	Yes:100	Yes :50	Best
C4	0.1597	0.2888	0.3322	0.2693	0.1815	0.2972	0.3277	0.2694	F = 50	No	Yes:100	Yes :50	Best
C25*	0.1375	0.3053	0.3107	0.2621	0.1533	0.3111	0.3094	0.2654	F = 100	No	no	Yes :50	Best
C28	0.2075	0.3135	0.3122	0.2822	0.1843	0.2907	0.3174	0.2673	F = 50	No	no	Yes :50	Best
Tests when WMA filter is applied													
C23	0.3395	0.41	0.3929	0.384					F = 100	Yes	Yes:100	Yes :50	Median
C24	0.3438	0.4172	0.4593	0.3946					F = 50	Yes	Yes:100	Yes :50	Median
C33	0.2128	0.3362	0.3225	0.3022					F = 100	Yes	no	Yes :50	Best
C34	0.2993	0.4205	0.4019	0.3785					F = 50	Yes	no	Yes :50	Best

Table 6.3: An overview of influence of WMA filter on normal walk results

Tests when WMA filter is not applied													
	Equal Error Rate-Expermient A				Equal Error Rate-Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER	T-Interpolation	Filter	C-normalize	C-deletion	T-cycle BestMedian
C1	0.1482	0.3285	0.3318	0.2792	0.1456	0.2922	0.3021	0.2503	F = 100	No	Yes:100	Yes :50	Best
C19	0.1494	0.357	0.3507	0.2935	0.1626	0.3348	0.2967	0.2589	F = 100	No	Yes:100	Yes :80	Best
C20	0.1509	0.3147	0.3227	0.2689	0.1590	0.3061	0.3130	0.2540	F = 100	No	Yes:100	Yes :30	Best

Table 6.4: An overview of influence of threshold value on results

Tests when normalization method is applied													
	Equal Error Rate-Expermient A				Equal Error Rate-Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER	T-Interpolation	Filter	C-normalize	C-deletion	T-cycle BestMedian
C1	0.1482	0.3285	0.3318	0.2792	0.1456	0.2922	0.3021	0.2503	F = 100	No	Yes:100	Yes :50	Best
C7	0.3229	0.4158	0.4235	0.3875					F = 100	No	Yes:100	Yes :50	Median

Table 6.5: A comparison of results obtained by using best and median cycles as typical cycles

steps to cover the same distance as covered in normal walk. Due to this reason we have 22 to 27 steps detected by the cycle detection method. Details about the tests and EER values as results of experiment A and B are given in A.2 on page 67. From this table it is clear that results of experiment B are worse than the ones of experiment A when length normalization method is used. Without length normalization method we see a minute improvement in the result of experiment B. Best results achieved in these experiments are given in table 6.6. Best results are achieved with interpolation frequency of 40. Here, we see same day results at interpolation frequency 40 are better but cross day results are same as with interpolation frequency 100. Again here, test (C23, C24, C33 and C34) show that WMA filter does not improve the results. If we compare C1 with (C19, C20) and with (C13, C14 and C15) we will find that a threshold 50 to delete unusual cycles and cycle length normalization at 100 are ideal, respectively. All best results shown in table 6.6 are achieved when best cycles (closest cycles) are used as typical cycles.

Slow Walk Best Result								
	Normalized							
	Equal Error Rates -Experiment A				Equal Error Rates -Experiment B			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C1	0.2741	0.3522	0.3529	0.3320	0.3124	0.3598	0.3724	0.3549
C2	0.2943	0.3398	0.3282	0.3288	0.2755	0.3467	0.3563	0.3329
C5	0.2116	0.3531	0.3512	0.3072	0.2373	0.3720	0.3451	0.3446

Table 6.6: Slow walk best result (refer table 6.1 on page 45 for best settings)

6.3.3 Fast Walk on Carpeted Surface

In contrast to the previous situation subjects were asked to walk faster than normal, which results in less number of cycles. Once again interpolation frequency of 100 have achieved best results. Tests (C23, C24, C33 and C34) where WMA filter was applied, did not improve the results. If we compare experiment A results of tests (C1, C19 and C20) we will find that for these tests all parameter settings are same except threshold of unusual cycle deletion. Results of these test show that threshold 50 has better results. Tests (C1, C13, C14 and C15) have same settings except the cycle length normalization and results of these tests show that changing length normalization does not significantly improve or worsen those results. Results of tests C1 to C12 show that best typical cycles have better results than the median typical cycles. Comparison of first six tests when normalization method is applied to the first six tests when normalization method is not applied, shows that results of both groups are same. Details about the results of experiment and tests conducted on fast walk are given in table A.3 on page 68 along with the comparison of results of the experiment A and experiment B. Best results of experiment A and B are given in table 6.7.

Fast walk Best Results								
				Normalized				
	Equal Error Rate - Experiment A				Equal Error Rate - Experiment B			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C5	0.1855	0.3381	0.3445	0.3056	0.2182	0.3636	0.3449	0.3185
				Not Normalized				
C25	0.2229	0.3401	0.3502	0.3015	0.2157	0.3490	0.3544	0.3175
C32	0.2151	0.3393	0.3578	0.2976	0.2141	0.3500	0.3486	0.3169

Table 6.7: Best results of fast walk (refer table 6.1 on page 45 for best settings)

6.3.4 Normal Walk on Grass

This is our fourth scenario where subjects were asked to walk normally on the grass as shown in figure 5.4(b). Comparison of results of tests C1 to C6 with C25 to C30 shows that tests with cycle length normalization have better results. Exactly, like previous walk setting tests with best typical cycles have better results than the tests with median typical cycles. Tests with WMA filter again have worse results, threshold of value 50 and normalizing the cycles to length 100 have good results as compare to all other settings. Best results of grass walk are given in table 6.8. Table A.2 on page 69 of appendix A shows the results of experiment A and experiment B. Here, almost all results (same day, cross day and joint EER) of all tests are better than result of experiment B.

Grass Walk Best Results								
				Normalized				
	Equal Error rate - Experiment A				Equal Error Rate - Experiment B			
Tests	EER1	EER2	EER3	J-EER	EER1	EER2	EER3	J-EER
C6	0.2715	0.361	0.3783	0.3359	0.3157	0.3485	0.4045	0.3594
C16	0.2714	0.3804	0.346	0.3292	0.2443	0.3818	0.3618	0.3327
				Not Normalized				
C26	0.322	0.3539	0.341	0.3391	0.2349	0.3602	0.3841	0.3349

Table 6.8: Best results of fast walk (refer table 6.1 on page 45 for best settings)

6.3.5 Normal Walk on Gravel Surface

Under this scenario subjects were asked to walk normally on the gravel surface as shown in figure 5.4(c). Results of gravel walk under (experiment A and experiment B) are given in table A.5 on page 70, from results its clear that same day EER1 results are much better than all other walk setting results. However, cross day results (EER2 and EER3) are same as the results of other walks settings. Here again interpolation frequency of 100 have better results as compared to other interpolation frequencies. Once again WMA filter did not help to improve the results. Best results of gravel walk are given in table 6.9. Tests which have produces best results have same parameter settings except the threshold value used to delete the cycles. Slight variation in threshold value have minute impact on the results. Comparing equal error rates of both experiments show that same day results of experiment B are better however, cross day results and joint EER of experiment A have better values.

Gravel Walk Best Results								
	Normalized Walk							
Tests	Equal Error Rate-Experiment A				Equal Error Rate-Experiment B			
	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C1	0.12	0.3265	0.3205	0.2545	0.1097	0.3632	0.3521	0.2807
C19	0.1134	0.3213	0.3165	0.2556	0.0978	0.3507	0.3471	0.2671
C20	0.1246	0.3322	0.3131	0.2558	0.1144	0.3690	0.3557	0.2856

Table 6.9: Best results of gravel walk (refer table 6.1 on page 45 for best settings)

6.3.6 Normal Walk on Inclined Surface

Under this scenario the subjects were asked to walk normally on an inclined grassy surface as shown in picture 5.4(d). Experiment A results of inclined walk of experiment A and B are given in table A.6 on page 71. From results first time this happened that EER2 is better then EER1. Actually this is because walk one and three were recorded when subject was going uphill and walk two and four were recorded when subject was coming downhill. Therefore, EER2 which is result of applying majority voting on pairwise distance metrics obtained form walk1 and walk3 (going uphill) have better results. EER1 and EER3 are the results from uphill and downhill walks. Best results of hill walk are given in table 6.10. Interpolation frequency 100 have produced better results as compared to other interpolation frequencies used in these tests. However, same day, cross day and joint EER results of all tests conducted under experiment A and experiment B have worse results as compared to all other walk settings.

Hill Walk Best Results								
				Normalized				
	Equal Error Rates				Equal Error Rates using Remained Cycles			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C14	0.3786	0.3674	0.4179	0.3976	0.3920	0.3390	0.4284	0.3905
				Not Normalized				
C25	0.3733	0.353	0.4286	0.3688	0.3721	0.3498	0.3981	0.3653
C32	0.3724	0.3518	0.4274	0.3696	0.3725	0.3343	0.3923	0.3677

Table 6.10: Best results of hill walk (refer table 6.1 on page 45 for best settings)

6.4 Comparison of Best Results of Different Walk Settings

This section will present two comparisons of best results shown in above section 6.3. In first comparison the best results of different walking speeds (normal, fast and slow walk) are compared. Second comparison is based on best results of different surfaces (carpeted, grass, gravel and inclined).

6.4.1 Comparison of Walk Speeds

Comparison of different walking speeds tells us that normal walk has better inter, intra day and joint EER results than the fast and slow walk and fast walk have better results than the slow walk. Same day results vary between 14% to 29% and cross day results vary between 29 to 35%. Joint EER varies between 25% to 30%. These results are shown in table. 6.11 Figure 6.3 shows DET curves based on best joint EER values shown in table 6.11 on the following page.

6.4.2 Comparison of Different Surfaces

Table 6.12 shows the comparison of normal walk results on different surfaces. In these scenarios all subjects walked normally on four different under-grounds i.e. carpeted, grass, gravel and inclined surface.

Normal Walk								
				Normalized				
	Equal Error Rates - Experiment A				Equal Error Rate - Expermient B			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER
C13	0.1626	0.2939	0.2821	0.2534	0.1752	0.2696	0.2848	0.2481
C16	0.1648	0.2893	0.3105	0.2664	0.1694	0.2944	0.3287	0.267
				Not Normalized				
C25	0.1375	0.3053	0.3107	0.2621	0.1533	0.3111	0.3094	0.2654
Fast Walk								
				Normalized				
	Equal Error Rates - Experiment A				Equal Error Rate - Expermient B			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER
C5	0.1855	0.3381	0.3445	0.3056	0.2182	0.3636	0.3449	0.3185
				Not Normalized				
C25	0.2229	0.3401	0.3502	0.3015	0.2157	0.3490	0.3544	0.3175
C32	0.2151	0.3393	0.35778	0.2976	0.2141	0.3500	0.3486	0.3169
Slow Walk								
				Normalized				
	Equal Error Rates -Experiment A				EERs using Remained Cycles			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C1	0.2741	0.3522	0.3529	0.3320	0.3124	0.3598	0.3724	0.3549
C2	0.2943	0.3398	0.3282	0.3288	0.2755	0.3467	0.3563	0.3329
C5	0.2116	0.3531	0.3512	0.3072	0.2373	0.3720	0.3451	0.3446

Table 6.11: Comparison of best results of different walking speeds (refer table 6.1 on page 45 for best settings)

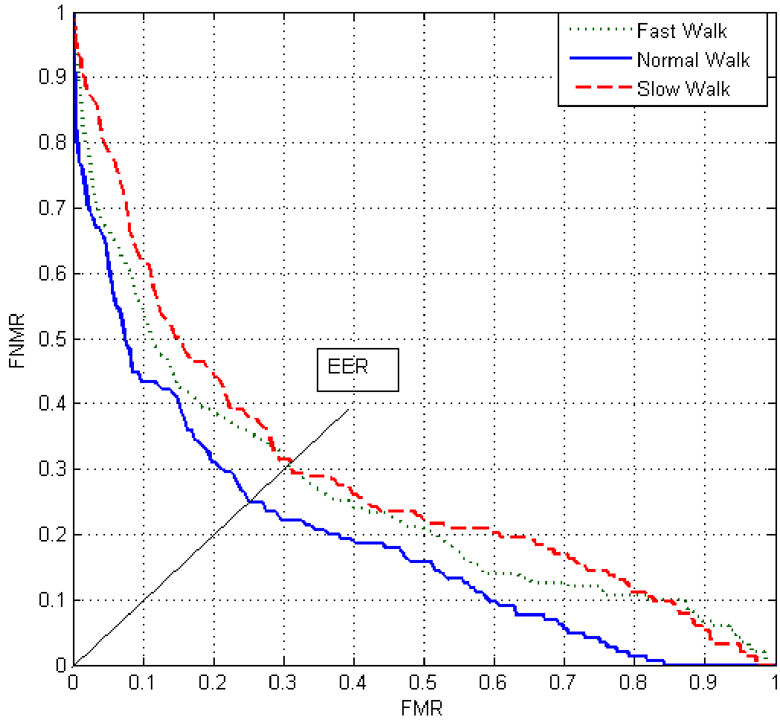

Figure 6.3: Comparison of different walking speeds with help of DET curves

Carpeted Surface								
				Normalized				
	Equal Error Rates -Experiment A				EERs using Remained Cycles			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C13	0.1626	0.2939	0.2821	0.2534	0.1752	0.2696	0.2848	0.2481
C16	0.1648	0.2893	0.3105	0.2664	0.1694	0.2944	0.3287	0.267
				Not Normalized				
C25	0.1375	0.3053	0.3107	0.2621	0.1533	0.3111	0.3094	0.2654
Gravel Surface								
				Normalized				
	Equal Error Rates -Experiment A				EERs using Remained Cycles			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C1	0.12	0.3265	0.3205	0.2545	0.1097	0.3632	0.3521	0.2807
C19	0.1134	0.3213	0.3165	0.2556	0.0978	0.3507	0.3471	0.2671
C20	0.1246	0.3322	0.3131	0.2558	0.1144	0.3690	0.3557	0.2856
Grassy Surface								
				Normalized				
	Equal Error Rates -Experiment A				EERs using Remained Cycles			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
C6	0.2715	0.361	0.3783	0.3359	0.3157	0.3485	0.4045	0.3594
				Not Normalized				
C16	0.2714	0.3804	0.346	0.3292	0.2443	0.3818	0.3618	0.3327
C26	0.322	0.3539	0.341	0.3391	0.2771	0.3587	0.3507	0.3305
Inclined Surface								
				Normalized				
	Equal Error Rates -Experiment A				EERs using Remained Cycles			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER
				Normalized				
C14	0.3786	0.3674	0.4179	0.3976	0.3920	0.3390	0.4284	0.3905
				Not Normalized				
C25	0.3733	0.353	0.4286	0.3688	0.3727	0.3347	0.3931	0.3677
C32	0.3724	0.3518	0.4274	0.3696	0.3725	0.3343	0.3923	0.3677

Table 6.12: Comparison of normal walk on different under-grounds (refer table 6.1 on page 45 for best settings)

In all these scenarios normal walk on carpeted surface has overall better results however, gravel walk has better same day results as compared to the normal walk on carpeted surface. As we know, cross day results have more importance than the same day results therefore, we can say that results of normal walk on carpeted surface are better than the results of normal walk on the gravel surface. If we go further we will find that normal walk results on gravel surface are better than normal walk results on grass and inclined surface. Normal walk on grass has better results than normal walk on inclined grassy surface. Under these experiments same day results varies between 9.78% to 39% and cross day results varies between 28% to 42%. Joint EER varies between 25% to 39%. Figure 6.4 shows a comparison of normal walk on different surfaces with help of DET curves.

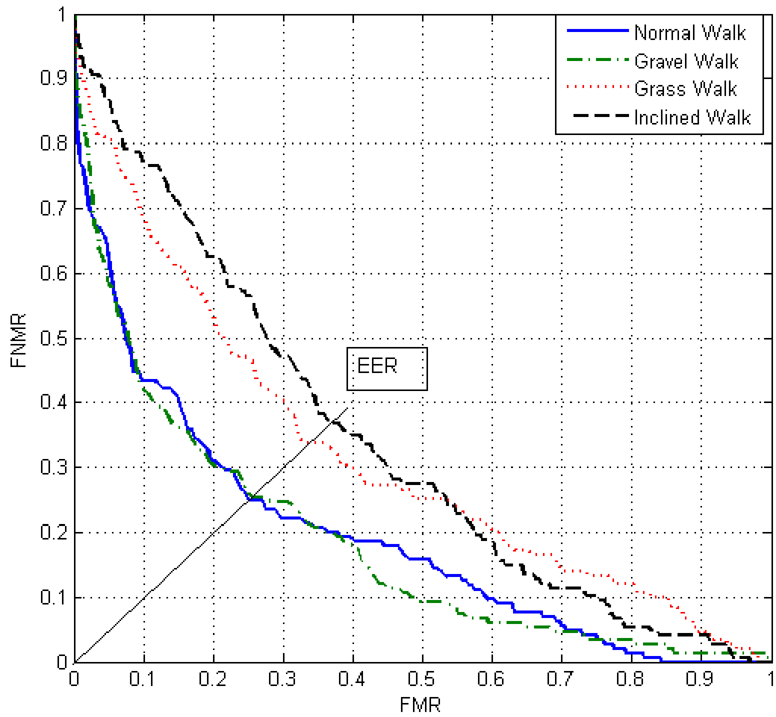

Figure 6.4: Comparison of normal walk speed on different surfaces with help of DET curves

6.4.3 Influence of Different Parameter Settings

This is our second research question and if we see results of tests conducted under any walk setting it will be clear that parameter settings of different methods, used in various tests conducted in this thesis influence the results. Results of six different walk settings presented in section 6.3, show that time interpolation with frequency 100, cycle normalization with length 100, threshold value of 50 to delete unusual cycles and best typical cycles have produced best results. However, WMA filter and median typical cycles have degraded the performance.

6.5 Results Comparison of This Study and Previous Studies

To author's knowledge, none of the previous studies have explored the influence of different walking surfaces on gait performance. Therefore, in following tables only comparison of result of different walk speeds is shown. In table 6.13 a comparison of normal results of same day is shown. Same database was used for all these studies.

Study	Methods	FMR %	FNMR %	(FMR+FNMR)%
Derawi et al.[19]	Cycle extraction	20.1	20.1	40.2
Nickel et al.[67]	Hidden Markov	9.31	10.42	19.73
Brandt [9]	Hidden Markov	0.91	2.08	2.99
This Study	Cycle extraction	13.75	13.75	27.5

Table 6.13: Comparison of normal walk results of cross day scenario for the first two studies and same day scenario for the last two studies. Phone base accelerometer is used in all these studies and placement of phone was on right hip

In this table 6.14 results of slow walks are compared with previous study. In this study mobile phones accelerometer sensor with sampling rate of 40 is used whereas, in other study dedicated motion recording sensor is used which have sampling rate of 100. Table 6.15 shows a comparison of fast walk results of same day.

Study	Sensor Type	Sensor Position	Methods	EER%
Holien [33]	dedicated	Hip	Walk extraction	10.35
This Study	Phone	Hip	Walk extraction	21.16

Table 6.14: Comparison of same day results of slow with previous study

Study	Sensor Type	Sensor Position	Methods	EER%
Holien [33]	dedicated	Hip	Walk extraction	3.15
This Study	Phone	Hip	Walk extraction	18.55

Table 6.15: Comparison of same day results of fast walk with previous study

Chapter 7

Conclusion and Future Work

7.1 Conclusion

According to estimations, there are five billion mobile subscriptions in the world, out of seven billion population by the end of year 2010. In developing countries the numbers of mobile users are growing very fast. Nowadays, a lot of mobile phones are reported lost or stolen in the state of no authentication. Therefore, personal data on lost or stolen mobile phones can easily be accessed. Mobile phones come with a conventional password based authentication system but mobile users are not willing to use this conventional method of authentication. Therefore, unobtrusive nature of biometric gait makes it a really suitable authentication system for mobile devices and for other scenarios where convenience is a problem. Biometric gait is a new dimension of biometric authentication systems. Gait authentication is not mature enough like other biometric authentication systems e.g. fingerprints or face, in sense of performance. Gait authentication can be established using machine vision, floor sensor based, accelerometer sensor-based approach. Gait authentication using wearable accelerometer sensor based approach is relatively younger than other two approaches and explored first time in 2005. Gait authentication can also be used in fusion with other authentication technologies (e.g. face recognition or fingerprints) to achieve multi modal authentication system, which can be very effective, where the primary authentication system fails e.g. face recognition fails due to worse (e.g. low light or fog) environmental conditions.

Nowadays, mobile phones are equipped with accelerometer sensor, which can be used for gait authentication purposes without any further requirement of wearing dedicated accelerometers. Therefore, the cost of deploying this new gait authentication system is subject to development of new software. The low-cost factor of gait authentication could lead it to a wide adoption across various vendors and operating systems.

In this thesis, we have explored wearable accelerometer-based approach in biometric gait recognition and for this purpose built-in accelerometer sensor of an android plate form based smartphone is used. Every subject walked with three different speeds (slow, normal and fast) and on four different surfaces (flat carpeted, grass, gravel and inclined surface). Acceleration data is collected using an application. Typical cycle extraction approach is adapted to extract typical cycle for each subject from the data collected of 48 subjects. This is first attempt to study the influence of different walking speeds and surfaces on gait performance using the built-in accelerometer of a cell phone and typical cycle approach. Two experiments A and B with 34 and 22 tests respectively, were carried out. EER values of each test is recorded to figure out best results and with which methods and parameter settings these best results are achieved. Considering future applications of gait recognition, experiments of this thesis was carefully designed to distinguish between same-day and cross-day's results. For different walking speeds, same day results vary between 14% to 29%, and cross day results vary between 29 to 35%. Similarly, for different surfaces, same-day results vary between 9.78% to 39%, and cross day results vary between 28% to 42%. From the comparison of results of different walking speeds and surfaces, variation in results is easily noticeable. Looking at the results of different tests conducted under one walk setting its clear that different parameter settings of methods used for analysis of data influence the results. From these results, it is proven that there is a huge difference in same-day results and cross day results. Unfortunately, the issue of same-day and cross-day results is not explored in previous studies on the wearable accelerometer based gait recognition except [9][66][25]. Therefore, in previous studies a question is left unanswered that results shown are also valid for cross day performance or not. It is also difficult to compare results of this study with the results of previous studies on wearable sensor based approach as type of sensors used and methods to analyze the data captured using these sensors are different from each other. Similarly, results are also presented in different ways in different studies. There is a strong requirement of collection and publishing of gait sample database so that performance of various gait recognition approaches could be compared.

7.2 Future Work

Gait recognition using cell phone based accelerometer sensor, in wearable sensor category is a novel approach with lot of aspects that require further research. In this thesis, we have explored six different circumstances (slow, fast, normal, grass surface, gravel surface, inclined surface) that influence human gait. It would be significant to explore some other scenarios, which are related to the topic of this thesis, e.g. going up and down the stairs, walking on sand and snow and influence of high heels. It would be interesting to see if human gait developed on sand and snow have same characteristics. In this thesis, we placed cell phone inside a pouch attached to the left side of the human body. Recently, the usage of the pouch is highly reduced and cell phone users place their phones normally in different pockets of their trousers. Therefore, it would be important to test other variations such as, placement of the phone and orientation of the phone inside the pocket or pouch. Results of this study show that different walking speeds influence gait recognition. Therefore, exploring automatic activity recognition (i.e person is sitting, standing still, walking with slow fast and normal velocity) would be interesting. All previous studies under the wearable sensor category focused on the influence of activity variations natural environmental conditions and health conditions. As these conditions highly influence gait recognition therefore, it is necessary to design solution, which could bring gait recognition closer to the practical implementations by solving the issues.

There is a requirement of developing new algorithms, which could primarily ensure the quality of accelerometer data at the runtime so that data with low sampling rate and time lag could be ignored before this data is used by the verification process. As we know, Different mobile phone based accelerometer sensors have different sampling rates. It would be interesting to explore the influence of sampling rates of different mobile phone based accelerometer sensors on gait performance.

Appendix A

Parameter Details and Results

In this appendix, details about the parameters of different methods and EER values achieved as a result of applying different tests on the extracted walks.

A.1 Details about parameters

This section will explain the important parameters of different methods. Almost all parameters depend upon the normalization frequency. From the result tables given in section A.2, it is clear that changing any of these parameters effects the results.

A.1.1 Interpolation

Interpolation frequency: frequency at which the resulting signal will be interpolated. It can be any arbitrary number but in our case in different tests frequency varies between 30-100.

A.1.2 Estimation of Cycle Length

This method have two parameters to set, detail about these parameters is given below:

- min-peak-height: Salient vector entries are compared against this parameter, if the entry of the salient vector is greater than the value of this parameter then this entry is assumed as a cycle start and later used for computation of cycle length. Value of this parameter is calculated by this formula 0.8 * interpolation frequency.

- min-peak-distance: Only those peaks in salient vector which have a distance of at-least min-peak-distance are considered. It is calculated by 0.5 * interpolation frequency.

A.1.3 Cycle Detection

Cycle detection methods takes in four parameters, their detail is given below:

- irregular cycles: this parameter is used to determine when a cycle is called irregular and it is calculated by 0.2 * interpolation frequency.
- min-peak-height: The entry in salient vector is compared against this parameter, if the entry if salient vector is greater than the value of this parameter then this entry is assumed as cycle start and later used for computation of cycle length 0.7 * interpolation frequency.
- too-long-cycles-peakheight: Minimum peak height used when dividing too long cycles: 0.4* interpolation frequency.
- too-long-distance: when dividing too long cycles those cycles form min/max salience vectors are removed which are away than too-long-distance 0.3 * interpolation frequency.

A.1.4 Deletion of Unusual Cycles

Threshold: when DTW distance of a cycle is to al least half of the other cycles is above this threshold value the cycle will be removed. Value of this parameter can be any arbitrary number but, in our case this value varies between 30-80

A.1.5 Cycle Normalization

Length: Cycles will be normalized to this length. This parameter can also be any arbitrary number however, in our case this value varies between 80 to 120.

A.2 Complete Results and comparison of Experiment A and Experiment B

Tables presented in this section have same columns as of table 6.1 on page 45. Only those columns which have no changing values i.e. S-choice: Signal choice, Z-normalization: centering around zero and L-estimation: estimation of cycle length are removed.

Tests when normalization method is applied													
	Equal Error Rate-Expermient A				Equal Error Rate-Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER	T-Interpolation	Filter	C-normalize	C-deletion	T-cycle BestMedian
C1	0.1482	0.3285	0.3318	0.2792	0.1456	0.2922	0.3021	0.2503	F = 100	No	Yes:100	Yes :50	Best
C2	0.2015	0.2799	0.3343	0.2588	0.1866	0.2496	0.3057	0.2457	F = 80	No	Yes:100	Yes :50	Best
C3	0.1722	0.349	0.299	0.2848	0.1871	0.2937	0.3107	0.2645	F = 60	No	Yes:100	Yes :50	Best
C4	0.1597	0.2888	0.3322	0.2693	0.1815	0.2972	0.3277	0.2694	F = 50	No	Yes:100	Yes :50	Best
C5	0.1626	0.3324	0.333	0.2682	0.1648	0.3193	0.3569	0.2669	F = 40	No	Yes:100	Yes :50	Best
C6	0.2083	0.3596	0.3339	0.3057	0.2398	0.3578	0.3291	0.3117	F = 30	No	Yes:100	Yes :50	Best
C7	0.3229	0.4158	0.4235	0.3875					F = 100	No	Yes:100	Yes :50	Median
C8	0.3255	0.3705	0.3876	0.3612					F = 80	No	Yes:100	Yes :50	Median
C9	0.3435	0.412	0.4246	0.3911					F = 60	No	Yes:100	Yes :50	Median
C10	0.2912	0.3897	0.3961	0.358					F = 50	No	Yes:100	Yes :50	Median
C11	0.3367	0.413	0.4271	0.3916					F = 40	No	Yes:100	Yes :50	Median
C12	0.4284	0.4333	0.4273	0.4275					F = 30	No	Yes:100	Yes :50	Median
C13*	0.1626	0.2939	0.2821	0.2534	0.1752	0.2696	0.2848	0.2481	F = 100	No	Yes:120	Yes :50	Best
C14	0.1407	0.3487	0.3322	0.2802	0.1616	0.3313	0.2820	0.2546	F = 100	No	Yes:80	Yes :50	Best
C15	0.2632	0.3802	0.3911	0.3411	0.2032	0.3263	0.3229	0.2960	F = 100	No	Yes:40	Yes :50	Best
C16*	0.1648	0.2893	0.3105	0.2664	0.1694	0.2944	0.3287	0.2670	F = 50	No	Yes:120	Yes :50	Best
C17	0.1913	0.2706	0.3514	0.2689	0.1567	0.2700	0.3274	0.2417	F = 50	No	Yes:80	Yes :50	Best
C18	0.1915	0.3309	0.3835	0.3079	0.1792	0.2902	0.3361	0.2836	F = 50	No	Yes:40	Yes :50	Best
C19	0.1494	0.357	0.3507	0.2935	0.1626	0.3348	0.2967	0.2589	F = 100	No	Yes:100	Yes :80	Best
C20	0.1509	0.3147	0.3227	0.2689	0.1590	0.3061	0.3130	0.2540	F = 100	No	Yes:100	Yes :30	Best
C21	0.3289	0.4263	0.3954	0.3723					F = 100	No	Yes:100	Yes :80	Median
C22	0.3063	0.3991	0.388	0.3588					F = 100	No	Yes:100	Yes :30	Median
C23	0.3395	0.41	0.3929	0.384					F = 100	Yes	Yes:100	Yes :50	Median
C24	0.3438	0.4172	0.4593	0.3946					F = 50	Yes	Yes:100	Yes :50	Median
Tests when normalization method is not applied													
	Equal Error Rate-Expermient A				Equal Error Rate-Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	JointEER	T-Interpolation	Filter	C-normalize	C-deletion	T-cycle BestMedian
C25*	0.1375	0.3053	0.3107	0.2621	0.1533	0.3111	0.3094	0.2654	F = 100	No	no	Yes :50	Best
C26	0.1805	0.3328	0.3315	0.2871	0.1996	0.2984	0.2984	0.2663	F = 80	No	no	Yes :50	Best
C27	0.1809	0.341	0.321	0.2802	0.1924	0.3202	0.3313	0.2829	F = 60	No	no	Yes :50	Best
C28	0.2075	0.3135	0.3122	0.2822	0.1843	0.2907	0.3174	0.2673	F = 50	No	no	Yes :50	Best
C29	0.2213	0.3769	0.3518	0.3151	0.1913	0.3610	0.3122	0.2889	F = 40	No	no	Yes :50	Best
C30	0.2657	0.3653	0.3535	0.3228	0.2202	0.3333	0.3741	0.3010	F = 30	No	no	Yes :50	Best
C31	0.142	0.3509	0.3333	0.2859	0.1641	0.2913	0.2863	0.2449	F = 100	No	no	Yes :80	Best
C32	0.1492	0.3031	0.327	0.2615	0.1575	0.3008	0.3170	0.2631	F = 100	No	no	Yes :30	Best
C33	0.2128	0.3362	0.3225	0.3022					F = 100	Yes	no	Yes :50	Best
C34	0.2993	0.4205	0.4019	0.3785					F = 50	Yes	no	Yes :50	Best

Table A.1: An overview of results of normal walk. Results marked with * are considered best

Normalized Walks													
	Equal Error Rate - Expermient A				Equal Error Rate - Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	WMA Filter	C-normalize	C-deletion	T-cycle Best/Median
C1*	0.2741	0.3522	0.3529	0.3320	0.3124	0.3598	0.3724	0.3549	F = 100	No	Yes:100	Yes :50	Best
C2*	0.2943	0.3398	0.3282	0.3288	0.2755	0.3467	0.3563	0.3329	F = 80	No	Yes:100	Yes :50	Best
C3	0.2741	0.3231	0.3714	0.3246	0.2939	0.3418	0.3827	0.3408	F = 60	No	Yes:100	Yes :50	Best
C4	0.2557	0.3824	0.3822	0.3612	0.2576	0.3635	0.3492	0.3399	F = 50	No	Yes:100	Yes :50	Best
C5*	0.2116	0.3531	0.3512	0.3072	0.2373	0.3720	0.3451	0.3446	F = 40	No	Yes:100	Yes :50	Best
C6	0.2267	0.3529	0.3678	0.3327	0.2275	0.3935	0.3720	0.3293	F = 30	No	Yes:100	Yes :50	Best
C7	0.4288	0.4265	0.4410	0.4335					F = 100	No	Yes:100	Yes :50	Median
C8	0.4176	0.4045	0.4390	0.4227					F = 80	No	Yes:100	Yes :50	Median
C9	0.4057	0.4200	0.4506	0.4244					F = 60	No	Yes:100	Yes :50	Median
C10	0.3880	0.4308	0.4402	0.4171					F = 50	No	Yes:100	Yes :50	Median
C11	0.3323	0.5433	0.4681	0.4239					F = 40	No	Yes:100	Yes :50	Median
C12	0.3143	0.5234	0.4693	0.4376					F = 30	No	Yes:100	Yes :50	Median
C13	0.2939	0.3824	0.3727	0.3567	0.2947	0.3925	0.3661	0.3569	F = 100	No	Yes:120	Yes :50	Best
C14	0.2943	0.3925	0.3629	0.3501	0.2949	0.3792	0.3810	0.3648	F = 100	No	Yes:80	Yes :50	Best
C15	0.3275	0.3927	0.4102	0.3704	0.3192	0.4104	0.4129	0.3769	F = 100	No	Yes:40	Yes :50	Best
C16	0.2496	0.3720	0.3669	0.3358	0.2524	0.3588	0.3671	0.3422	F = 50	No	Yes:120	Yes :50	Best
C17	0.2237	0.3522	0.3531	0.3290	0.2369	0.3718	0.3592	0.3421	F = 50	No	Yes:80	Yes :50	Best
C18	0.2786	0.3737	0.3988	0.3597	0.2992	0.3718	0.3924	0.3644	F = 50	No	Yes:40	Yes :50	Best
C19	0.3092	0.3537	0.3731	0.3470	0.2922	0.3631	0.3984	0.3558	F = 100	No	Yes:100	Yes :80	Best
C20	0.3022	0.3727	0.3531	0.3406	0.2933	0.3843	0.3569	0.3514	F = 100	No	Yes:100	Yes :30	Best
C21	0.4096	0.4324	0.4559	0.4302					F = 50	No	Yes:100	Yes :80	Median
C22	0.3604	0.3876	0.4561	0.3899					F = 50	No	Yes:100	Yes :30	Median
C23	0.3478	0.4147	0.4582	0.4104					F = 100	Yes	Yes:100	Yes :50	Median
C24	0.3573	0.3931	0.4071	0.3850					F = 40	Yes	Yes:100	Yes :50	Median
Not Normalized Walks													
	Equal Error Rate - Expermient A				Equal Error Rate - Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	WMA Filter	C-normalize	C-deletion	T-cycle Best/Median
C25	0.2747	0.3773	0.3731	0.3541	0.2714	0.3659	0.3445	0.3372	F = 100	No	no	Yes :50	Best
C26	0.2553	0.3518	0.3875	0.3398	0.2857	0.3512	0.3504	0.3303	F = 80	No	no	Yes :50	Best
C27	0.3335	0.3727	0.4114	0.3739	0.3129	0.3625	0.4035	0.3729	F = 60	No	no	Yes :50	Best
C28	0.2563	0.3716	0.3480	0.3393	0.2763	0.3857	0.3780	0.3542	F = 50	No	no	Yes :50	Best
C29	0.2424	0.3804	0.4110	0.3752	0.2343	0.3865	0.3765	0.3306	F = 40	No	no	Yes :50	Best
C30	0.3139	0.3924	0.4314	0.3731	0.2673	0.3782	0.3967	0.3581	F = 30	No	no	Yes :50	Best
C31	0.2959	0.3727	0.3541	0.3475					F = 100	No	no	Yes :80	Best
C32	0.2939	0.3727	0.3592	0.3522					F = 100	No	no	Yes :30	Best
C33	0.2351	0.3686	0.3735	0.3374					F = 100	Yes	no	Yes :50	Best
C34	0.3218	0.3859	0.3582	0.3533					F = 40	Yes	no	Yes :50	Best

Table A.2: An overview of results of slow walk

Normalized Walks													
	Equal Error Rate - Experiment A				Equal Error Rate - Experiment B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	Filter	C-normalize	C-deletion	T-Cycle Best/Median
C1	0.1935	0.3806	0.354	0.314	0.1741	0.3604	0.3594	0.3096	F = 100	No	Yes:100	Yes :50	Best
C2	0.2161	0.3766	0.3648	0.3239	0.1827	0.3550	0.3910	0.3243	F = 80	No	Yes:100	Yes :50	Best
C3	0.1957	0.3576	0.38	0.3248	0.1796	0.3544	0.3594	0.3236	F = 60	No	Yes:100	Yes :50	Best
C4	0.2169	0.4093	0.3528	0.3175	0.1916	0.3584	0.3814	0.3104	F = 50	No	Yes:100	Yes :50	Best
C5*	0.1855	0.3381	0.3445	0.3056	0.2182	0.3636	0.3449	0.3185	F = 40	No	Yes:100	Yes :50	Best
C6	0.2525	0.3608	0.3712	0.3293	0.2384	0.3468	0.4020	0.3275	F = 30	No	Yes:100	Yes :50	Best
C7	0.3384	0.3642	0.3584	0.3537					F = 100	No	Yes:100	Yes :50	Median
C8	0.3375	0.3209	0.3846	0.3486					F = 80	No	Yes:100	Yes :50	Median
C9	0.2918	0.3808	0.3728	0.3542					F = 60	No	Yes:100	Yes :50	Median
C10	0.2729	0.3802	0.3844	0.3549					F = 50	No	Yes:100	Yes :50	Median
C11	0.2894	0.3415	0.3736	0.339					F = 40	No	Yes:100	Yes :50	Median
C12	0.2925	0.3794	0.3788	0.3504					F = 30	No	Yes:100	Yes :50	Median
C13	0.1902	0.3608	0.3586	0.2997	0.1790	.37440	.37440	.3068	F = 100	No	Yes:120	Yes :50	Best
C14	0.1961	0.3792	0.4002	0.3199	0.1698	.36120	0.3804	0.3028	F = 100	No	Yes:80	Yes :50	Best
C15	0.1947	0.368	0.3808	0.3318	0.2337	0.3878	0.3880	0.3285	F = 100	no	Yes:40	Yes :50	Best
C16	0.2202	0.3994	0.3862	0.3425	0.20690	0.4004	0.3782	0.3782	F = 50	No	Yes:120	Yes :50	Best
C17	0.2341	0.3638	0.3792	0.3314	0.19350	0.3413	0.3584	0.3086	F = 50	No	Yes:80	Yes :50	Best
C18	0.2927	0.4	0.396	0.3569	0.2525	0.3808	0.3804	0.3340	F = 50	No	Yes:40	Yes :50	Best
C19	0.1888	0.4008	0.3612	0.3246	0.1620	0.3628	0.3502	0.3173	F = 100	No	Yes:100	Yes :80	Best
C20	0.1953	0.3704	0.3724	0.3292	0.2341	0.3902	0.3896	0.3302	F = 100	No	Yes:100	Yes :30	Best
C21	0.3127	0.3812	0.3856	0.3607					F = 50	No	Yes:100	Yes :80	Median
C22	0.2755	0.3816	0.3878	0.3552					F = 50	No	Yes:100	Yes :30	Median
C23	0.3333	0.3776	0.376	0.3642					F = 100	Yes	Yes:100	Yes :50	Median
C24	0.2386	0.3359	0.3476	0.3099					F = 50	Yes	Yes:100	Yes :50	Median

Not Normalized Walks													
	Equal Error Rate - Experiment A				Equal Error Rate - Experiment B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-Interpolation	Filter	C-normalize	C-deletion	T-Cycle Best/Median
C25*	0.2229	0.3401	0.3502	0.3015	0.2157	0.3490	0.3544	0.3175	F = 100	No	no	Yes :50	Best
C26	0.2043	0.3664	0.379	0.3141	0.1778	0.3678	0.3912	0.3331	F = 80	No	no	Yes :50	Best
C27	0.2288	0.3405	0.3796	0.3236	0.2543	0.3422	0.4008	0.3220	F = 60	No	no	Yes :50	Best
C28	0.2353	0.3798	0.3758	0.3302	0.2229	0.3872	0.3762	0.3314	F = 50	No	no	Yes :50	Best
C29	0.2398	0.3506	0.3602	0.3283	0.2475	0.3317	0.3403	0.3106	F = 40	No	no	Yes :50	Best
C30	0.222	0.3147	0.3642	0.3171	0.2333	0.3327	0.3952	0.3203	F = 30	No	no	Yes :50	Best
C31	0.2343	0.36	0.359	0.3097	0.2025	0.3391	0.3606	0.3132	F = 100	No	no	Yes :80	Best
C32*	0.2151	0.3393	0.35778	0.2976	0.2141	0.3500	0.3486	0.3169	F = 100	No	no	Yes :30	Best
C33	0.2055	0.3544	0.3399	0.3244					F = 100	Yes	no	Yes :50	Best
C34	0.2718	0.3592	0.3508	0.3372					F = 50	Yes	no	Yes :50	Best

Table A.3: An overview of results of fast walk

Normalized Walks													
	Equal Error Rate - Expermient A				Equal Error Rate - Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	Filter	C-normalize	C-deletion	T-cycle Best/Median
C1	0.2896	0.3492	0.3703	0.3404	0.2496	0.3581	0.3450	0.3176	F = 100	No	Yes:100	Yes :50	Best
C2	0.2824	0.3549	0.3908	0.3379	0.2271	0.3406	0.3831	0.3249	F = 80	No	Yes:100	Yes :50	Best
C3	0.2675	0.4191	0.4193	0.3678	0.2549	0.3847	0.3824	0.3440	F = 60	No	Yes:100	Yes :50	Best
C4	0.2557	0.3896	0.3585	0.3417	0.2529	0.3841	0.3816	0.3456	F = 50	No	Yes:100	Yes :50	Best
C5	0.2782	0.3573	0.3902	0.3538	0.2467	0.3558	0.3521	0.3151	F = 40	No	Yes:100	Yes :50	Best
C6*	0.2715	0.361	0.3783	0.3359	0.3157	0.3485	0.4045	0.3594	F = 30	No	Yes:100	Yes :50	Best
C7	0.3612	0.4514	0.4237	0.4011					F = 100	No	Yes:100	Yes :50	Median
C8	0.3731	0.4193	0.4326	0.4141					F = 80	No	Yes:100	Yes :50	Median
C9	0.3727	0.4276	0.4704	0.4298					F = 60	No	Yes:100	Yes :50	Median
C10	0.3233	0.411	0.4195	0.3909					F = 50	No	Yes:100	Yes :50	Median
C11	0.2635	0.3841	0.4083	0.3615					F = 40	No	Yes:100	Yes :50	Median
C12	0.3443	0.4726	0.4638	0.4277					F = 30	No	Yes:100	Yes :50	Median
C13	0.2549	0.3694	0.4094	0.3611	0.2296	0.3436	0.3687	0.3334	F = 100	No	Yes:120	Yes :50	Best
C14	0.2939	0.3655	0.3789	0.3397	0.2345	0.3646	0.3491	0.3121	F = 100	No	Yes:80	Yes :50	Best
C15	0.3131	0.3396	0.3963	0.3504	0.2916	0.3554	0.3711	0.3278	F = 100	No	Yes:40	Yes :50	Best
C16*	0.2714	0.3804	0.346	0.3292	0.2443	0.3818	0.3618	0.3327	F = 40	No	Yes:120	Yes :50	Best
C17	0.2737	0.4005	0.4201	0.363	0.2339	0.3965	0.3900	0.3601	F = 40	No	Yes:80	Yes :50	Best
C18	0.2735	0.3845	0.3725	0.3386	0.2614	0.4018	0.4046	0.3637	F = 40	No	Yes:40	Yes :50	Best
C19	0.2743	0.3408	0.3746	0.3399	0.2308	0.3608	0.3273	0.3016	F = 100	No	Yes:100	Yes :80	Best
C20	0.2904	0.3498	0.3727	0.3417	0.2508	0.3602	0.3485	0.3178	F = 100	No	Yes:100	Yes :30	Best
C21	0.3718	0.4197	0.4596	0.4205					F = 50	No	Yes:100	Yes :80	Median
C22	0.3518	0.4336	0.4389	0.4129					F = 50	No	Yes:100	Yes :30	Median
C23	0.4078	0.451	0.4528	0.4431					F = 100	Yes	Yes:100	Yes :50	Median
C24	0.4112	0.3946	0.4748	0.4229					F = 40	Yes	Yes:100	Yes :50	Median
Not Normalized Walks													
	Equal Error Rate - Expermient A				Equal Error Rate - Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	Filter	C-normalize	C-deletion	T-cycle Best/Median
C25	0.2671	0.3608	0.3915	0.3345	0.2349	0.3602	0.3841	0.3349	F = 100	No	no	Yes :50	Best
C26*	0.322	0.3539	0.341	0.3391	0.2771	0.3587	0.3507	0.3305	F = 80	No	no	Yes :50	Best
C27	0.3325	0.4003	0.4253	0.3926	0.3133	0.3396	0.4091	0.3772	F = 60	No	no	Yes :50	Best
C28	0.2651	0.3814	0.4005	0.3551	0.2745	0.4009	0.3560	0.3369	F = 50	No	no	Yes :50	Best
C29	0.2635	0.3841	0.4083	0.3615	0.2357	0.4080	0.3941	0.3394	F = 40	No	no	Yes :50	Best
C30	0.2748	0.3797	0.4207	0.3616	0.2925	0.3592	0.4090	0.3789	F = 30	No	no	Yes :50	Best
C31	0.2665	0.3589	0.4029	0.3418	0.2565	0.4090	0.3691	0.3258	F = 100	No	no	Yes :80	Best
C32	0.2671	0.3612	0.3995	0.3359	0.2367	0.3499	0.3862	0.3368	F = 100	No	no	Yes :30	Best
C33	0.2747	0.3592	0.3791	0.3246					F = 100	Yes	no	Yes :50	Best
C34	0.2635	0.3841	0.4083	0.3615					F = 40	Yes	no	Yes :50	Best

Table A.4: An overview of results of grass walk

Normalized Walks													
	Equal Error Rate - Expermient A				Equal Error Rate - Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	Filter	C-normalize	C-deletion	T-cycle Best/Median
C1*	0.12	0.3265	0.3205	0.2545	0.1097	0.3632	0.3521	0.2807	F = 100	No	Yes:100	Yes :50	Best
C2	0.122	0.3421	0.3499	0.2831	0.1392	0.3456	0.3764	0.3003	F = 80	No	Yes:100	Yes :50	Best
C3	0.1622	0.3477	0.38	0.3182	0.1474	0.3692	0.3633	0.2959	F = 60	No	Yes:100	Yes :50	Best
C4	0.1606	0.3423	0.3794	0.2892	0.1548	0.3654	0.3818	0.3184	F = 50	No	Yes:100	Yes :50	Best
C5	0.184	0.34	0.3856	0.2993	0.2074	0.3402	0.3945	0.3015	F = 40	No	Yes:100	Yes :50	Best
C6	0.1994	0.3535	0.4007	0.3119	0.2204	0.3617	0.4202	0.3249	F = 30	No	Yes:100	Yes :50	Best
C7	0.3594	0.4473	0.4146	0.4121					F = 100	No	Yes:100	Yes :50	Median
C8	0.3889	0.4411	0.4598	0.4308					F = 80	No	Yes:100	Yes :50	Median
C9	0.2505	0.3935	0.4506	0.3643					F = 60	No	Yes:100	Yes :50	Median
C10	0.2802	0.3947	0.4538	0.372					F = 50	No	Yes:100	Yes :50	Median
C11	0.2602	0.3876	0.4699	0.3865					F = 40	No	Yes:100	Yes :50	Median
C12	0.2988	0.3788	0.4372	0.3752					F = 30	No	Yes:100	Yes :50	Median
C13	0.1142	0.3386	0.3643	0.2853	0.1212	0.3712	0.3822	0.2963	F = 100	No	Yes:120	Yes :50	Best
C14	0.1668	0.344	0.3805	0.2946	0.1319	0.3547	0.3410	0.2814	F = 100	No	Yes:80	Yes :50	Best
C15	0.2212	0.4268	0.3587	0.32	0.1928	0.3603	0.3587	0.3074	F = 100	No	Yes:40	Yes :50	Best
C16	0.172	0.3497	0.4001	0.3098	0.1644	0.3398	0.3947	0.3041	F = 50	No	Yes:120	Yes :50	Best
C17	0.1846	0.3845	0.4005	0.3397	0.1689	0.3543	0.4176	0.3094	F = 50	No	Yes:80	Yes :50	Best
C18	0.2326	0.3796	0.3845	0.3363	0.2034	0.3818	0.4031	0.3279	F = 50	No	Yes:40	Yes :50	Best
C19*	0.1134	0.3213	0.3165	0.2556	0.0978	0.3507	0.3471	0.2671	F = 100	No	Yes:100	Yes :80	Best
C20*	0.1246	0.3322	0.3131	0.2558	0.1144	0.3690	0.3557	0.2856	F = 100	No	Yes:100	Yes :30	Best
C21	0.2246	0.3796	0.4455	0.365					F = 50	No	Yes:100	Yes :80	Median
C22	0.2596	0.3895	0.4455	0.3681					F = 50	No	Yes:100	Yes :30	Median
C23	0.339	0.3995	0.5038	0.405					F = 100	Yes	Yes:100	Yes :50	Median
C24	0.2326	0.3796	0.3854	0.3363					F = 40	Yes	Yes:100	Yes :50	Median
Not Normalized Walks													
	Equal Error Rate - Expermient A				Equal Error Rate - Expermient B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	Filter	C-normalize	C-deletion	T-cycle Best/Median
C25	0.1466	0.3509	0.384	0.3038	0.1558	0.3533	0.3822	0.2942	F = 100	No	no	Yes :50	Best
C26	0.1502	0.3459	0.4053	0.3008	0.1412	0.3350	0.3997	0.2980	F = 80	No	no	Yes :50	Best
C27	0.179	0.3808	0.3846	0.3115	0.1808	0.3284	0.4086	0.3057	F = 60	No	no	Yes :50	Best
C28	0.2099	0.3653	0.3591	0.3021	0.1690	0.3499	0.3603	0.2948	F = 50	No	no	Yes :50	Best
C29	0.2358	0.371	0.3931	0.3498	0.2402	0.3987	0.3927	0.3396	F = 40	No	no	Yes :50	Best
C30	0.2408	0.3997	0.4122	0.354	0.2754	0.4049	0.4190	0.3630	F = 30	No	no	Yes :50	Best
C31	0.141	0.3237	0.3806	0.2854	0.1340	0.3354	0.3625	0.2798	F = 100	No	no	Yes :80	Best
C32	0.1491	0.3482	0.3832	0.2986	0.1598	0.3515	0.3623	0.2887	F = 100	No	no	Yes :30	Best
C33	0.1596	0.3394	0.4041	0.2998					F = 100	Yes	no	Yes :50	Best
C34	0.3127	0.3812	0.4061	0.3567					F = 40	Yes	no	Yes :50	Best

Table A.5: An overview of results of Gravel walk

Normalized Walks														
	Equal Error Rate - Experiment A				Equal Error Rate - Experiment B				Preprocessing		Typical Cycle Extraction			
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	WMA Filter	C-normalize	C-deletion	T-cycle Best/Median	
C1	0.4002	0.3933	0.4502	0.4087	0.3843	0.3770	0.4290	0.4002	F = 100	No	Yes:100	Yes :50	Best	
C2	0.4037	0.3876	0.4386	0.4075	0.3716	0.3544	0.4366	0.3842	F = 80	No	Yes:100	Yes :50	Best	
C3	0.3531	0.382	0.4679	0.4014	0.3588	0.3546	0.4577	0.3830	F = 60	No	Yes:100	Yes :50	Best	
C4	0.3859	0.3476	0.4278	0.461	0.3324	0.3365	0.4181	0.3748	F = 50	No	Yes:100	Yes :50	Best	
C5	0.3914	0.3894	0.4892	0.4245	0.4176	0.3697	0.4815	0.4422	F = 40	No	Yes:100	Yes :50	Best	
C6	0.4306	0.04235	0.4331	0.4233	0.3792	0.3935	0.4228	0.3950	F = 30	No	Yes:100	Yes :50	Best	
C7	0.4192	0.3731	0.4646	0.4351					F = 100	No	Yes:100	Yes :50	Median	
C8	0.4148	0.3959	0.4605	0.437					F = 80	No	Yes:100	Yes :50	Median	
C9	0.5102	0.4494	0.4774	0.4864					F = 60	No	Yes:100	Yes :50	Median	
C10	0.4302	0.3764	0.4534	0.4302					F = 50	No	Yes:100	Yes :50	Median	
C11	0.4496	0.4278	0.4984	0.4531					F = 40	No	Yes:100	Yes :50	Median	
C12	0.4092	0.4053	0.4434	0.4199					F = 30	No	Yes:100	Yes :50	Median	
C13	0.421	0.3918	0.4494	0.4171	0.4008	0.3678	0.4384	0.4073	F = 100	No	Yes:120	Yes :50	Best	
C14*	0.3786	0.3674	0.4179	0.3976	0.3920	0.3390	0.4284	0.3905	F = 100	No	Yes:80	Yes :50	Best	
C15	0.3918	0.3672	0.4412	0.4	0.4057	0.3556	0.4093	0.4014	F = 100	No	Yes:40	Yes :50	Best	
C16	0.3863	0.3985	0.4687	0.4081	0.4125	0.4120	0.4557	0.4328	F = 50	No	Yes:120	Yes :50	Best	
C17	0.379	0.402	0.4632	0.4183	0.3778	0.4038	0.4687	0.4203	F = 50	No	Yes:80	Yes :50	Best	
C18	0.3902	0.3921	0.4288	0.4015	0.3925	0.3878	0.4356	0.4116	F = 50	No	Yes:40	Yes :50	Best	
C19	0.3718	0.3882	0.4354	0.3861	0.3853	0.3744	0.4298	0.3953	F = 100	No	Yes:100	Yes :80	Best	
C20	0.4002	0.3835	0.4502	0.4028	0.3835	0.3770	0.4292	0.4000	F = 100	No	Yes:100	Yes :30	Best	
C21	0.4467	0.4038	0.489	0.4365					F = 50	No	Yes:100	Yes :80	Median	
C22	0.4504	0.429	0.5012	0.4574					F = 50	No	Yes:100	Yes :30	Median	
C23	0.4316	0.4181	0.4768	0.4532					F = 100	Yes	Yes:100	Yes :50	Median	
C24	0.4637	0.4158	0.4652	0.4437					F = 40	Yes	Yes:100	Yes :50	Median	

Not Normalized Walks													
	Equal Error Rate - Experiment A				Equal Error Rate - Experiment B				Preprocessing		Typical Cycle Extraction		
Tests	EER1	EER2	EER3	Joint EER	EER1	EER2	EER3	Joint EER	T-interpolation	WMA Filter	C-normalize	C-deletion	T-cycle Best/Median
C25*	0.3733	0.353	0.4286	0.3688	0.3727	0.3347	0.3931	0.3677	F = 100	No	no	Yes :50	Best
C26	0.3806	0.4075	0.4075	0.3993	0.3531	0.3587	0.4113	0.3765	F = 80	No	no	Yes :50	Best
C27	0.3998	0.3581	0.4763	0.4055	0.3645	0.3479	0.4083	0.3745	F = 60	No	no	Yes :50	Best
C28	0.4037	0.367	0.4292	0.413	0.3869	0.3204	0.4272	0.3885	F = 50	No	no	Yes :50	Best
C29	0.422	0.4071	0.4705	0.4276	0.3965	0.3725	0.4502	0.4033	F = 40	No	no	Yes :50	Best
C30	0.3916	0.4396	0.4284	0.409	0.3510	0.3867	0.3626	0.3692	F = 30	No	no	Yes :50	Best
C31	0.3792	0.3483	0.4351	0.3833	0.3718	0.3591	0.4158	0.3759	F = 100	No	no	Yes :80	Best
C32*	0.3724	0.3518	0.4274	0.3696	0.3725	0.3343	0.3923	0.3677	F = 100	No	no	Yes :30	Best
C33	0.3861	0.3965	0.4191	0.4011					F = 100	Yes	no	Yes :50	Best
C34	0.391	0.0429	0.4886	0.4399					F = 40	Yes	no	Yes :50	Best

Table A.6: An overview of results of Hill walk

Appendix B

Biometric Performance Metrics

The content of appendix B on biometric performance was created by Prof. Dr. Christoph Busch's lecture "Biometric Systems" at the Hochschule Darmstadt, Germany. It is used here, with his consent.

B.1 Overview

- Metrics (FTC,FTX,FTE,FMR, FNMR, FAR, FRR, ROC, DET)
- Single vs. multiple attempt
- Similarity matrix
- confidence of measured error rates

B.2 Biometric Failures

There are multiple failure associated with a acquisition of a biometric sample or with its processing. In Sections B.3 to B.5 we will discuss the failures that are associated with the deficiency of a biometric system to create a biometric reference for a data subject and subsequently in Sections B.9 to B.10 will consider errors that are attributed to biometric verification and identification systems.

B.3 Failure-to-Capture

A Failure-to-Capture Rate (FTC) is constituted, when the capture process could not generate a biometric sample of sufficient quality. This can be caused due to one of the following reasons:

1. The sample is not generated, as the characteristic is not placed properly on the capture device (e.g finger not covering the sensor area)

2. The captured signal is rejected by the automatic sample quality control algorithm.

3. The captured signal is stored as file, but rejected by the operator (staff expert) subsequent to visual inspection as it is not of sufficient quality

The ISO-definition [37] for the FTC is given by:

Failure-to-Capture Rate: *proportion of failures of the biometric capture process to produce a captured biometric sample that is acceptable for use.*

To estimate the FTC we use the following formula:

$$FTC = \frac{N_{tca} + N_{nsq}}{N_{tot}} \tag{B.1}$$

where N_{tca} is the number of terminated capture attempts, N_{nsq} is the number of images created with insufficient sample quality and N_{tot} is the total number of capture attempts. In consequence of a Failure-to-Capture are new capture attempt is initiated. This is illustrated in figure B.1 .

B.4 Failure-to-eXtract

A Failure-to-eXtract is constituted, when the feature extraction process was not able to generate a biometric template. This can be caused due to one of the following reasons:

1. The algorithm itself declares that it cannot create a template from the input sample. This could be caused by a insufficient number of features that were identified e.g. only five minutia could be extracted from a fingerprint image.

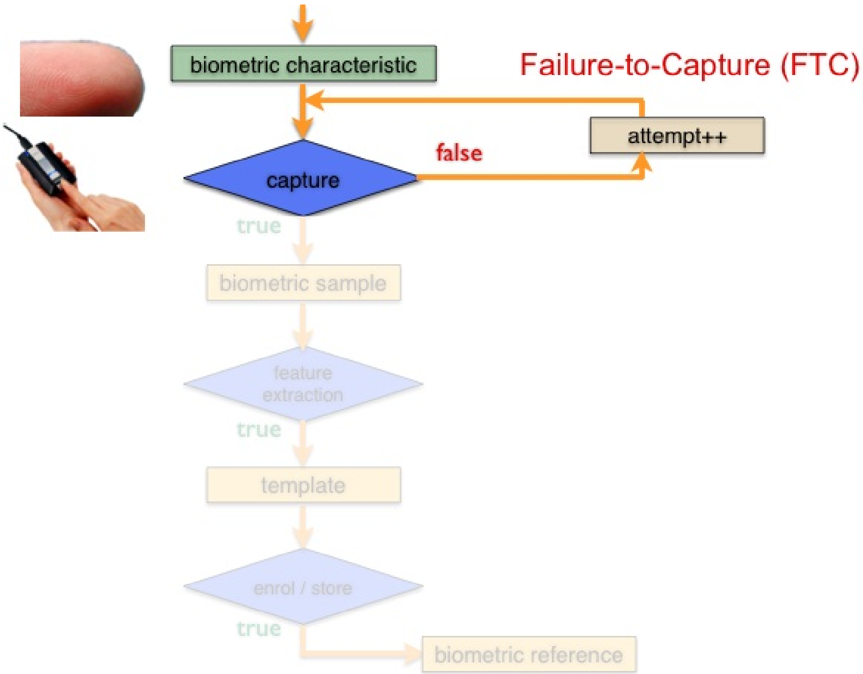

Figure B.1: Failure-to-Capture (FTC)

2. Processing time of feature extraction algorithm exceeds the specified limit and thus the feature extraction is terminated

3. The feature extraction algorithm might suddenly crash during processing. In this case, some actions will be undertaken (e.g. start over application, repeat process, etc.) but if the crash happens all the time with the same sample then for this image a failure to extract feature will be constituted. There is currently no ISO-definition for the Failure-to-eXtract Rate.

To estimate the Failure-to-eXtract Rate (FTX) we use the following formula:

$$FTX = \frac{N_{ngt}}{N_{sub}} \tag{B.2}$$

where N_{ngt} is the number of cases, where no template was generated and and N_{sub} is the total number of biometric samples being submitted to the feature extraction component (i.e. the template generator). In an operational scenario the consequence of a Failure-to-eXtract is a new attempt including a new biometric sample creation and it subsequent processing. This is illustrated in figure B.2 .

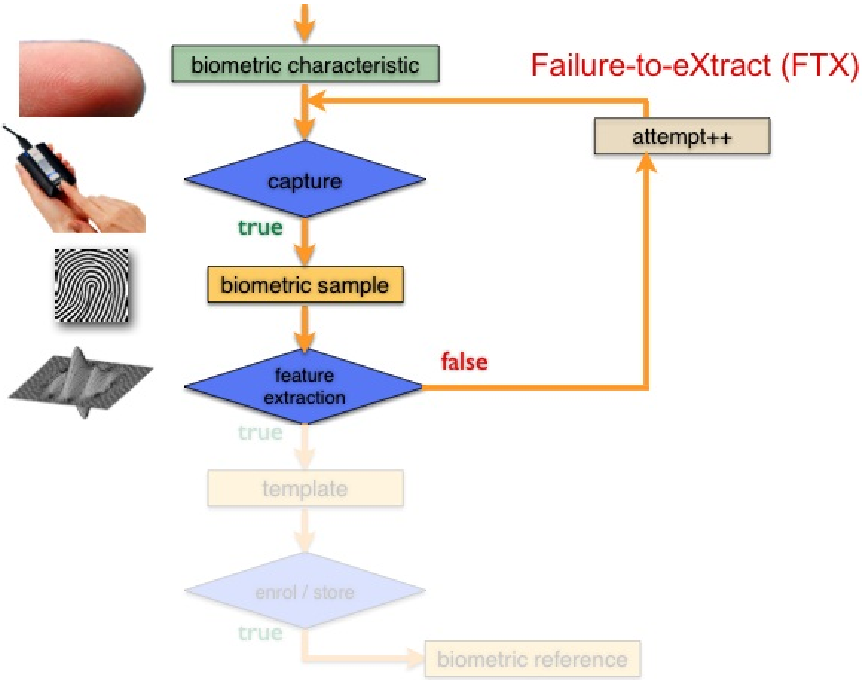

Figure B.2: Failure-to-eXtract (FTX)

B.5 Failure-to-Enrol

A Failure-to-Enrol is constituted, when the biometric system is not capable to create for data subject a biometric reference. Thus the Failure-to-Enrol Rate (FTE) expresses the proportion of the population, for which the system fails to complete the enrolment process. This can be caused due to one of the following reasons:

1. The biometric characteristic of the subject (e.g. its fingerprint images) can not be captured at all.

2. For each evaluation setting, and if required instances of the same characteristic (e.g. left index finger instead right index finger) it is not possible to create for this subject a template of sufficient quality (e.g. a feature set with minimum number of minutia)

There are currently two ISO-definitions for the FTE. The original definition in the performance testing standard [38] and the more recent one from the harmonized biometric vocabulary [37]:

Failure-to-Enol Rate (ISO 19795-1): *proportion of the population for whom the system fails to complete the enrolment process.*

Failure-to-Enrol Rate (ISO SC37 SD2): *proportion of biometric enrolment (that did not fail for non-biometric reasons), that resulted in a failure to create and store an enrolment data record for an eligible biometric capture subject, in accordance with an enrolment policy. .*

To estimate the FTE we use the following formula:

$$FTE = \frac{N_{nec}}{N} \tag{B.3}$$

where N_{nec} is the number of cases, where we meet one of the two Failure-to-Enrol criteria and N is the total number of subjects, intended to be enroled in the biometric application. The consequence of a Failure-to-Enrol In an operational scenario is that for the capture subject a fallback procedure must be activated that should treat the individual in a non-discriminatory manner. The Failure-to-Enrol is illustrated in figure B.3 .

B.6 Failure-to-Acquire

The Failure-to-Acquire Rate (FTA) is essential for the verification process and estimates the likelihood that biometric comparison can not be completed due to potential deficiencies in the live sample that is submitted as a probe. If there is no feature vector that can be compared to a biometric reference this can be caused due to one of the following reasons:

1. The is no biometric sample generated, which is expressed by the FTC.
2. The feature extraction componen failed to extract features as the number and/or quality of extracted features is not sufficient. This is expressed by the FTX.

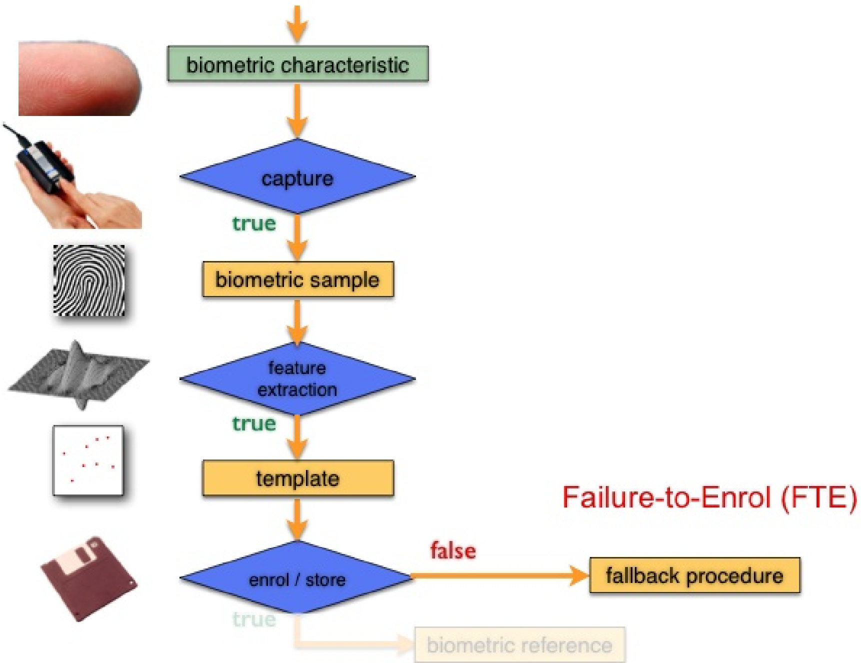

Figure B.3: Failure-to-Enrol (FTE)

There are currently two ISO-definitions for the FTA. The original definition in the performance testing standard [38] and the more recent one from the harmonized biometric vocabulary [37]:

Failure-to-Acquire Rate (ISO 19795-1): *proportion of verification or identification attempts for which the system fails to capture or locate an image or signal of sufficient quality.*

Failure-to-Acquire Rate (ISO SC37 SD2): *proportion of a specified set of probe acquisitions that failed to create a biometric probe.*

Note that in ISO SC37 SD2 a *probe* is defined as *biometric data input to an algorithm for comparison to a biometric reference(s)*.To estimate the Failure-to-Acquire Rate we use the following formula:

$$FTA = FTC + FTX * (1 - FTC) \tag{B.4}$$

B.7 False-Match

For imposter comparisons a False-Match constitutes the undesired case that an imposter probe is matching a biometric reference, which has not been created for himself. There are currently two ISO-definitions for the corresponding False-Match-Rate (FMR). The original definition in the performance testing standard [38] and the more recent one from the harmonized biometric vocabulary [37]:

False-Match-Rate (ISO 19795-1): *proportion of zero-effort impostor attempt samples falsely declared to match the compared non-self template.*

False-Match-Rate (ISO SC37 SD2): *proportion of the completed biometric non-match comparison trials that result in a false match.*

$$FMR(t) = \int_t^1 \Phi_i(s)ds \tag{B.5}$$

Together with the False-Non-Match-Rate (FNMR) the FMR is the key metric to be used in biometric technology testing and is understood to characterize a security property of a biometric system. Note that some literature is using the term False-Accept-Rate in the meaning of FMR.

B.8 False-Non-Match

For genuine comparisons a False-Non-Match constitutes the undesired case that an genuine probe is not matching to biometric reference, which has been created for the same subject from the same source (e.g. same index finger). There are currently two ISO-definitions for the corresponding False-Non-Match-Rate (FNMR). The original definition in the performance testing standard [38] and the more recent one from the harmonized biometric vocabulary [37]:

False-Non-Match-Rate (ISO 19795-1): *proportion of genuine attempt samples falsely declared not to match the template of the same characteristic from the same data subject supplying the sample.*

False-Non-Match-Rate (ISO SC37 SD2): *proportion of the completed biometric match comparison trials that result in a false non-match.*

$$FNMR(t) = \int_0^t \Phi_g(s)ds \tag{B.6}$$

Together with the False-Match-Rate (FMR) the FNMR is the key metric to be used in biometric technology testing and is understood to characterize a convenience property of a biometric system. Note that some literature is using the term False-Reject-Rate in the meaning of FNMR.

B.9 Verification System Performance

The first order estimation of the performance for a verification system that is based on transactions allowing multiple attempts can be derived from the detection error trade-off curve. However if this is applied the potential correlations between the attempts are neglected. Such correlations could be due to habituation of the capture subject with the human- computer interface of the biometric system. The relevant measures for a verification system are the False-Accept-Rate (FAR) and the False-Reject-Rate (FRR). The ISO-definition [38] for both metrics are the following:

False-Accept-Rate (ISO 19795-1): *proportion of verification transactions with wrongful claims of identity that are incorrectly confirmed.*

False-Reject-Rate (ISO 19795-1): *proportion of verification transactions with truthful claims of identity that are incorrectly denied.*

For the simplified case that the verification system does allow only a single attempt per transaction then the FAR and FRR can be estimated as follows.

$$FAR = FMR * (1 - FTA) \tag{B.7}$$

and

$$FRR = FTA + FNMR * (1 - FTA) \tag{B.8}$$

If the biometric application is likely to be confronted with a large number of failure to enrol cases (e.g. as it is a fingerprint system for mine workers) and the biometric performance shall be predicted based on a gallery that was collected for a technology testing then the equations B.7 and B.8 do not sufficiently express the performance to be expected. The reason for this is that in a technology evaluation biometric references are generated from the gallery that do not cause a failure-to-enrol and probes that do not cause a failure-to-acquire. For such a case the generalized versions of the above equations are more appropriate, which are given by:

$$GFAR = FMR * (1 - FTA) * (1 - FTE) \tag{B.9}$$

and

$$GFRR = FTE + (1 - FTE) * FTA + (1 - FTE) * (1 - FTA) * FNMR \tag{B.10}$$

B.10 Identification System Performance

The first order estimation of the false positive and false negative identification rates for open-set systems, can be derived from FMR and FNMR and the DET curve. However, such estimates cannot take account of correlations in the comparisons involving the same data subject, and consequently can be quite inaccuraten [**ISO-19795-1**].

$$FPIR = (1 - FTA) * (1 - (1 - FMR)^N) \tag{B.11}$$

where $FPRI$ is the False-Positive-Identification-Rate. For a small FMR we can substitue in equation B.11

$$(1 - FMR)^N \approx 1 - N * FMR \tag{B.12}$$

and thus under the assumption of $FTA = 0$ we derive

$$FPIR = (1 - 0) * (1 - (1 - N * FMR) \tag{B.13}$$

$$FPIR = N * FMR \tag{B.14}$$

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