



Gait Recognition Based on Angles Measurement

تمييز المشية اعتمادا على زوايا الحركة

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Authorization

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List of Figures

Figure 1-1: Abstract Design of Typical Biometric System [34].	3
Figure 1-2: Gait Phases [6].	8
Figure 1-3: General Process of Gait Recognition [28].	11
Figure 2-1 : User Authentication Approaches [16].	14
Figure 2-2: Five States of the Leg [25].	16
Figure 2-3: Bundle Rectangle [17].	16
Figure 2-4: Walking Subject with Stripe Painted on the Trouser [36].	19
Figure 3-1: A typical Gait Recognition Algorithm [20].	22
Figure 3-2: Image brightness histogram [11].	24
Figure 3-3: Image Brightness Histogram [28].	24
Figure 3-4: Many Lines Parameterize by a different ρ and θ [8].	27
Figure 3-5: Forward and Inverse DFT [9].	29
Figure 3-6: Classification of Various Types of Ground Imaging [42].	30
Figure 3-7: The Structure of a Bayes Network [33].	32
Figure 4-1: Overview of System Design.	35
Figure 4-2: First Phase of Gait Recognition Framework.	37
Figure 4-3: Second Phase of Gait Recognition Framework.	38
Figure 4-4: The Basic Structure of OpenCV Library [19].	39
Figure 4-5: Illustration of background subtraction using MoG.	40
Figure 4-6: Determining Stride Width.	42
Figure 4-7: Extra Lines that need to be eliminated.	45
Figure 4-8: Grid of Pixels.	46
Figure 4-9: Flowchart of Filter Lines Algorithm.	47
Figure 4-10: First Phase of Filter Lines Algorithm.	48
Figure 4-11: Second Phase of Filter Lines Algorithm.	49
Figure 4-12: Example of Shared Points on x Axis and y Axis.	49
Figure 4-13: Illustration of Filter A.	50
Figure 4-14: Illustration of Filter B.	51
Figure 4-15: Illustration of Filter C.	51
Figure 4-16: Flow chart of Filter C.	52
Figure 4-17: Sample thigh lines.	53

Figure 4-18: Illustration of Filter D.	54
Figure 4-19: Illustration of Filter E.	55
Figure 4-20: Feature Selection for One Gait Cycle.	56
Figure 5-1: Illustration of Data Acquisition Process.	58
Figure 5-2: Dynamic Change of Inclination of a Person Thigh.....	60
Figure 5-3: Dynamic Change of Inclination of a Person Leg.	61
Figure 5-4: Result of Applying Curve Fitting to Figure 5-2.	61
Figure 5-5: Result of applying curve fitting to Figure 5-3.	62
Figure 5-6: Fourier Spectrum for Thigh Inclination of Four Gaits of Same Person.	62
Figure 5-7: Fourier Spectrum for Leg Inclination of Four Gaits of Same Person.	63
Figure 5-8: Image of Gait Sequence.	64
Figure 5-9: Extracted Foreground Subject after the Background Subtraction.	66
Figure 5-10: Extracted Silhouette after the Silhouette Extraction Step.	66
Figure 5-11: Gait Cycle Detection.	66
Figure 5-12: Extracted Skeleton.	68
Figure 5-13: After Applying Hough Transform.	67
Figure 5-14: Dividing Walking Subject into Two Parts.	68
Figure 5-15: Extracted Lower Half of Body.	68
Figure 5-16: Overall Recognition Rate.	72

Abbreviation List

ANN	Artificial Neural Network
CV	Computer Vision
DFT	Discrete Fourier Transform
DNA	Deoxyribonucleic Acid
EER	Equal Error Rate
FLA	Filter Lines Algorithm
FN	False Negative
FP	False Positive
FS	Floor Sensor
GMM	Gaussian Mixture Model
HT	Hough Transform
KNN	K-Nearest Neighbor
MOG	Mixture of Gaussian
MR	Motion Recorder
MV	Machine Vision
NN	Neural Network
Pc	Precision
PPHT	Progressive Probabilistic Hough Transform
Rc	Recall
SHT	Standard Hough Transform
WS	Wearable Sensor

Table of Contents

List of Figures.....	V
Abbreviation List.....	VII
Table of Contents.....	VIII
Arabic summary	XI
Abstract	XII
CHAPTER ONE Introduction	1
Preface.....	1
Biometrics Recognition.....	1
Biometric System	2
Biometric Types.....	3
Gait Distinctions	5
Biometric Gait Definition.....	6
Gait Features	8
General Process of Gait Recognition	10
Statement of the Problem.....	11
Structure of the Thesis	12
CHAPTER TWO Literature Review.....	13
Related Work	13
Aim of the Thesis	20
CHAPTER THREE Background Theory of the Thesis.....	21
Typical Gait Recognition Algorithm	21
Background Subtraction.....	22
Frame Difference.....	24

Temporal Median Filter	25
Running Gaussian Average	25
Mixture of Gaussian (MoG)	26
Hough Transform	26
Discrete Fourier Transform (DFT)	28
Classification Techniques.....	29
Neural Networks.....	30
Decision Tree	31
Naïve Bayes	32
Support Vector Machine.....	33
K-Nearest Neighbor.....	34
CHAPTER FOUR Gait Recognition Design and Implementation	35
System Design	35
Gait Recognition Framework Implementation	36
OpenCv Library	37
Data Preprocessing.....	39
Background Subtraction	39
Silhouette Extraction	40
Gait Cycle Detection.....	41
Hough Line Transform.....	43
Filter Lines Algorithm.....	44
Feature Extraction	55
CHAPTER FIVE Experimental Results	58
Training Phase	58
Results of the Gait Recognition Algorithm.....	60

Testing Phase	69
CHAPTER SIX conclusion and future work	73
Conclusion	73
Future Work	73
References.....	75

Arabic summary

ملخص

لقد بات موضوع التعرف على المشية (Gait Recognition) مؤخراً من المواضيع التي ازداد الاهتمام بها ، لاسيما أن هذا المجال لا يزال يحتاج إلى الكثير من التطوير ، بالإضافة إلى أنه يطرح بعض الخصائص المتميزة مثل سهولة الالتقاط أو الحصول على البيانات بأقل كلفة و بدون الحاجة إلى الاتصال المباشر مع الشخص.

إن الأعمال السابقة في هذا المجال تتطلب إصاق شريط على لباس الشخص و ذلك لتسهيل استخراج الخطوط المستقيمة للأرجل، كما أنها تعاني من تدني معدل التعرف نسبياً. يقوم العمل المقترح في هذه الرسالة بالتغلب على مشكلة وجود الشريط على لباس الشخص.

إن العمل المقترح في هذه الرسالة يتألف من ثلاث مراحل. في المرحلة الأولى يتم استخراج الـ (Gait signature) من خلال تغير قيم الميل لكل من الفخذ والساق أثناء المشي. حيث تشمل المرحلة الأولى على (background subtraction) و (silhouette extraction) و احتساب دورة المشي. أما في المرحلة الثانية فيتم حذف الخطوط المستقيمة الزائدة في الصورة الهيكلية للشخص، لأن هذه الخطوط لا تمثل الميل الحقيقي لمستقيمات الأرجل. إن المرحلة الثانية تحتوي على (silhouette skeleton) و (Hough line transform) و (Filter Lines Algorithm) و (feature extraction). لقد تم اقتراح هذه الخوارزمية (FLA) لتقوم بتحديد و اختيار الخطوط المستقيمة التي تمثل كلاً من الفخذ و الساق. أما في المرحلة الثالثة يتم استخدام الـ (KNN) لتصنيف مشية الشخص و التعرف عليه.

و لاختبار أداء البرنامج للنظام المقترح ، تم التقاط مائة و ثمانٍ و عشرون مقطع فيديو لاثنين و ثلاثين شخص ، بمعدل أربع مقاطع لكل شخص. كما تم اختيار أربع و ستون مقطعاً لعمل (training) للبرنامج ، بينما الأربع و ستون مقطع الأخرى تم استخدامها كعينات إدخال لاختبار الأداء.

تشير النتائج التجريبية بالنهاية بالحصول على النسب التالية:

Accuracy	Recall	Precision
%90.63	%98.31	%90.63

إن هذا العمل المقدم يعتمد في حله على شكل الإنسان ، حيث يفترض أن كلاً من الفخذ والساق يقعان في النصف السفلي من الجسم ، كما يفترض أن الشخص يمشي على سطح أفقي أملس ، بمعنى أن كلاً من الفخذ و الساق لهما نفس الخط العمودي. بالنهاية يمكن التركيز بالمستقبل بالعمل على تطوير هذا النظام للتعامل مع حالة المشي على السطوح غير المستوية.

Abstract

Gait recognition has recently become one of the interesting topics since this field is still immature and poses distinctive characteristics. Characteristics include easy capturing, require low-cost tools, and do not require any contact with humans.

The reported algorithms in this field require using a stripe to be painted on the person clothes to facilitate the extraction of lines from the person's lower limb. They also were reported with low recognition rate. The work presented in this thesis overcomes the stripe painting difficulty.

The proposed gait recognition framework consists of three stages. In the first stage, gait signature is extracted from the dynamic change of inclination of the lower body parts; thigh and leg. First stage consists of background subtraction, silhouette extraction, and gait cycle computation. In the second stage, the undesirable extra lines in the resulted skeleton image from the first stage are eliminated since these lines do not represent the actual inclination lines of the lower extremity. Second stage consists of silhouette skeleton, Hough line transform, Filter Lines Algorithm, and feature extraction. In this work, Filter Lines Algorithm is proposed to filter out the extra lines and select only lines that represent thigh and leg of the walking person. The third stage uses K-Nearest Neighbor classifier to classify the walking person as unauthorized or authorized.

To test performance of the proposed gait recognition framework, four short videos are recorded for each one of thirty two persons resulting in one hundred and twenty eight videos. Sixty four videos are used to train the framework while the other sixty four are used to test performance of the proposed framework.

Experimental results indicate an accuracy, recall, and precision of 90.63%, 98.31%, and 90.63%, respectively. The proposed framework depends on human shape assuming the thigh and leg are within the lower half of human body. It also assumes that the person walking on a horizontally and smooth surface meaning that both thigh and leg have the same vertical line. Future work should focus on improving the framework to detect persons walking on uneven and non-smooth surfaces.

CHAPTER ONE

Introduction

Preface

Different systems for human identification were used recently. Gait recognition is one of these systems that do not need the cooperation of or contact with the person to be identified.

In order to form the identity access management, access control, and identifying individuals in surveillance area, one of the biometric methods must be used. The biometric methods are used uniquely to recognize people based on one or more intrinsic physical or behavioral features. Depending on these features, biometric methods are divided into two main classes:

- Physiological biometrics: recognition is based on fingerprint, iris, palm print, DNA, hand geometry, and face.
- Behavioral biometrics: recognition is based on typing rhythm, voice, and gait recognition.

Biometrics Recognition

The traditional methods for user recognition and authentication are based on a piece of information or code the person knows (password, PIN). Other methods are based on code the person has (key, magnetic card) [47]. These traditional methods are not reliable due to their dependency on something that can be forgotten, disclosed, or even stolen.

Recognizing person's reliably plays an important role in diverse business applications. This implies that a secure recognition should be based on something that characterizes the person [5]. Therefore, any identification system must involve features that are born with the person which is a biometric component to assure the identity of a given person.

Biometric System

A typical biometric system is comprised of five integrated components as shown in Figure 1-1. A sensor is used to collect the data and convert the received information into a digital form. Signal processing algorithms perform quality

control activities and used to develop the biometric template. A data storage component is used to keep the information that new biometric templates will be compared to (database). A matching algorithm compares the new biometric template to one or more templates kept in data storage. Finally, a decision process (either automated or human-assisted) uses the results from the matching component to make a system-level decision [46].

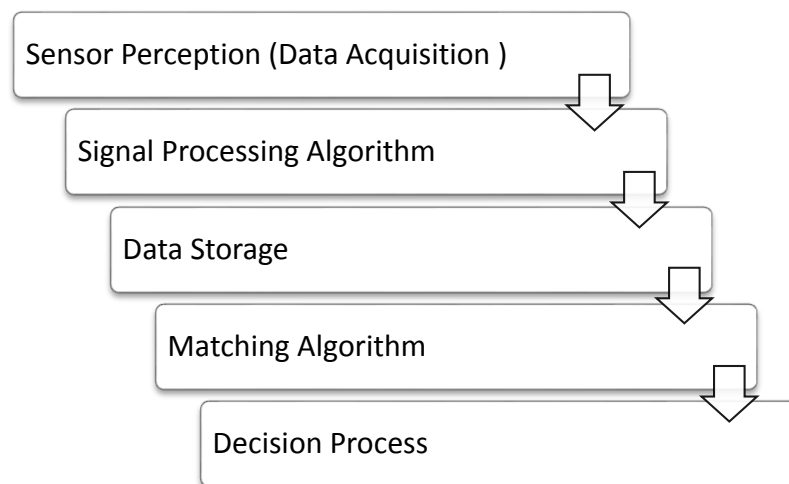


Figure 0-1: Abstract Design of Typical Biometric System [34].

Biometric Types

Generally speaking, biometrics are unique markers that identify or verify the identity of people using intrinsic physical or behavioral characteristics. Biometrics have been used regularly by criminal justice agencies to identify suspects for over a century [27].

Current biometric modalities include: Hand, Face, Fingerprint, Gait, Signature, Voice, Iris, Retina, Vein, DNA, Body Odor, Ear Pattern, Keystroke, and Lip [38]. Next, a brief overview of each one is shown.

1. **Hand Geometry:** Biometric hand recognition systems measure and analyze the overall structure, shape and proportions of the hand, e.g. length, width and thickness of the hand, fingers and joints, and characteristics of the skin surface area such as creases and ridges.
2. **Face Biometrics:** Specific features of a face include distance between the eyes, width of the nose, position of cheekbones, jaw line, chin, and so forth.
3. **Iris Biometrics:** uses high-resolution images of the ridges of the eye. The iris of the eye is well suited for authentication purposes. It is an internal organ protected from most damage and wear, it is practically flat and uniform under most conditions, and has a texture that is unique even to genetically identical twins.
4. **Voice Biometrics (known as speaker recognition):** a biometric modality that uses an individual's voice for verification and/or identification. Speaker recognition uses the acoustic features of speech that have been found to vary among individuals. These acoustic patterns reflect both anatomy (e.g. size and shape of the throat and mouth) and learned behavioral patterns (e.g. voice pitch, speaking style, tone, cadence and frequency of a person's voice).

- 5.
6. **Signature Biometrics:** uses the dynamic analysis of a signature to authenticate a person. Dynamic signature measures the speed and pressure an individual uses when signing his/her name and not what the signature itself looks like.
7. **Fingerprint Biometrics:** unique for each finger of a person including identical twins. The biometric fingerprint sensor takes a digital picture of a fingerprint. The fingerprint scan detects the ridges and valleys of a fingerprint and converts them into ones and zeros.
8. **Retina Biometrics:** retina, the layer of blood vessels situated at the back of the eye, forms a unique pattern. Retina biometrics is generally regarded as the most secure biometric method. Retina scanners compare the blood vessels in the eye. A scanning device that uses low light compares unique patterns on the retina.
9. **Vein Biometrics:** vein patterns on the eye's retina are known as one of the most unique characteristics owned by humans. This pattern is not genetically determined, but is randomly developed by each individual. The vein structure (vein tree) is captured using infrared light.
10. **DNA Biometrics:** DNA (DeoxyriboNucleic Acid) is the well-known double helix structure present in every human cell.
11. **Body Odor Biometrics:** a contactless physical biometric that attempts to confirm a person's identity by analyzing the olfactory properties of the human
12. **body scent.** According to the University of Cambridge, the sensors that have been developed are capable of capturing the body scent from nonintrusive body parts, such as the hand.
13. **Ear Pattern Biometrics:** shape of the outer ear, lobes, bone structure and the size are unique to each person.
14. **Keystroke Dynamics:** an automated method of examining an individual's keystrokes on a keyboard. The technology uses a keyboard compatible with PCs. This technology examines such dynamics as speed and pressure, total time of typing a particular password, and the time a user takes between hitting certain keys.

15. Lip Biometrics: normal lines and fissures in the form of wrinkles and grooves present in the zone of transition of human lip, between the inner labial mucosa and outer skin. The appearance of lip prints look like finger prints and vary from individual to individual.
16. Gait Biometrics: behavioral biometric and it can be defined simply as the way the person walks. Here, the gait signature is represented by the dynamic and static features extracted from gait cycle.

The scope of this thesis is focused on gait biometric. The next section provides the distinctive characteristic of the gait biometric.

Gait Distinctions

The first effort toward gait recognition in computer vision was probably by Niyogi and Adelson in the early 1990s [37]. Studying gait as a biometric is therefore considered relatively a new area of study.

According to the biometric resources, it has been found that iris print, fingerprint, palm print and hand geometry were systematically studied and employed in many systems. In spite of their widespread applications, these resources suffer from two main disadvantages. First, Failure to match in low resolution images (pictures taken at a distance). Second, necessity of user cooperation to get accurate results [14]. For these reasons, innovative biometric systems for human identification at distance have become an increasing demand in various significant applications. So the gait recognition has become the system that gained immense

attention among the computer vision community researchers in recent years; this is because of its attractive properties, where the acquisition of the data can be done easily with simple and low cost instrumentation and the perception can take place at a distance in surveillance area and even without awareness of the individual [26]. Finally, in this modern era, the integration of gait analysis and biometrics has fascinated several security-sensitive environments such as military, banks, parks and airports and has turned out to be a popular research direction [3].

Biometric Gait Definition

The most general definition of a biometric is defined as, [3]: A physiological or behavioral characteristic, which can be used to identify and verify the identity of an individual. The gait can simply be defined as the way in which the human body walks.

There are two main phases in the gait cycle, stance phase and swing phase [40]. During stance phase, the foot is on the ground, whereas in swing phase the same foot is no longer in contact with the ground. On the contrary, the leg is swinging through in preparation for the next foot strike. Depending on this description, the gait cycle traditionally has been divided into seven periods, four during stance phase and three during swing.

The names of these periods are self-descriptive and are based on the movement of the foot, as shown in Figure 1-2. The stance phase periods are as follows:

- 1) Loading response which begins with initial contact, or with heel strike, where the instant of the foot contacts the ground. Loading response ends with opposite toe off, when the opposite extremity leaves the ground.
- 2) Mid stance which begins with opposite toe off and ends when the centre of gravity is directly over the reference foot.
- 3) Terminal stance which begins when the centre of gravity is over the supporting foot and ends when the contralateral foot contacts the ground (opposite heel strike). During terminal stance, around 35 percent of the gait cycle, the heel rises from the ground.

- 4)
- 5) Pre-swing which begins at contralateral initial contact and ends at toe off, at around 60 percent of the gait cycle.

After the stance phase, swing phase starts directly, and it is divided into three periods:

- 1) Initial swing which begins at toe off and continues until maximum knee flexion (60 degrees) occurs.
- 2) Midswing which begins when the foot passes directly beneath the body (feet adjacent) coincidental with midstance for the other foot and ends at the tibia is vertical or perpendicular to the ground.
- 3) Terminal swing which begins where the tibia is vertical and ends at initial contact of the reference foot.

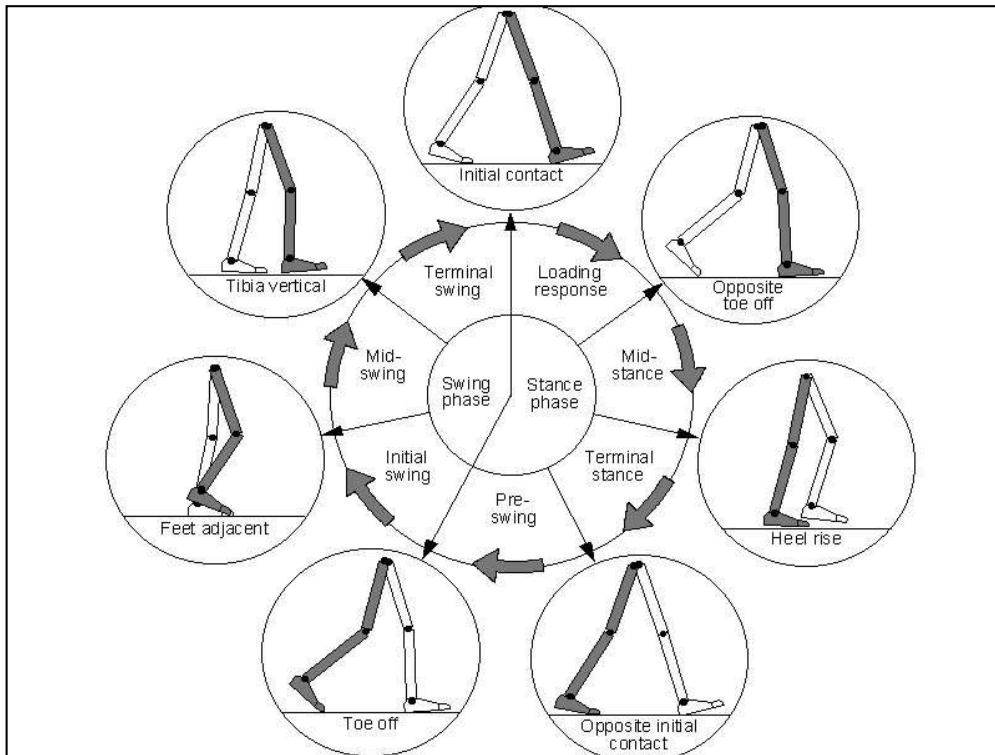


Figure 0-2: Gait Phases [6].

The approximate timing for the seven periods of gait cycle is:

1. Loading response (0-10%).
2. Midstance (10-30%).
3. Terminal stance (30-50%).
4. Preswing (50-60%).
5. Initial Swing (60-70%).
6. Midswing (70-85%).
7. Terminal swing (85-100%).

Gait Features

Features of the gait form the gait signature which can be used for human gait recognition. These features can be broadly classified into two categories, namely static and dynamic cues. The static features reflect the geometry based measurements of the anatomical structure of the human body such as the person's

height and the length or width of the different body segments. Static features can be derived from the observed gait such as the stride length, whilst the dynamic features are the cues which describe the kinematics of the locomotion process, such as the angular motion of the lower limbs extracted from the joint trajectory data.

The extraction of static cues requires less effort with low computational complexity. This indicates that recognizing people using static features, such as the stride and body height is straightforward. Recent research on gait using static features for identification proved that a promising recognition rate can be achieved [25]. On the other hand, some researchers have preferred to fuse both static and dynamic cues with a belief that fusion would yield the optimal gait recognition rate. Although a high recognition rate was reported, it was clearly noted that the body-related parameters are not robust since they are highly dependent on clothing of the walking subjects [48].

Despite the fact that static features have been proved by recent experiments to achieve promising gait recognition rates, their use for the development of a biometric system is impractical. This is mainly because static features are dependent on clothing, bags, and other factors which will certainly affect the recognition performance [48]. On the other hand, Cutting et al. [12] showed that dynamic features contribute significantly more in human recognition than static cues such as height and concluded that kinematic information is important for gender

Classification whereas static features are insufficient to reveal the gender of the walking subject. In addition to that, from dynamic aspect side, anyone can observe that there is a harmonic compatibility in the movement of the lower extremity thighs and legs. Therefore, the proposed approach focuses on the inclinations of thigh and leg that appear through gait cycle in lower extremity which represent this harmonic movement, consequently providing unique features for gait recognition. It is worth mentioning that until this moment, gait has not been considered as a replacement for traditional authentication mechanisms (passwords, fingerprints, etc.) but rather a complementary biometric. As in a multi-modal biometric system, gait helps to increase the accuracy of the system [16].

General Process of Gait Recognition

Figure 1-3 shows the main stages (or modules) that are being used by most gait recognition methods. These are:

- A. Preprocessing module: very important pre-processing step in many computer vision applications. Accurate retrieval of the foreground objects are vital in order to minimize distortion or inaccuracies [3], which can often include reduce noise, enhance the signal, detect the moving person, track the moving person, background subtraction, silhouette extraction, normalization, and scaling.
- B. Feature extraction/measurement: choose which features to extract and how. It includes gait cycle detect, spatiotemporal correlation, and similarity computation.
- C. Pattern classification: measuring the distances in some space in which the patterns are represented, consequently identifying the person.

D.

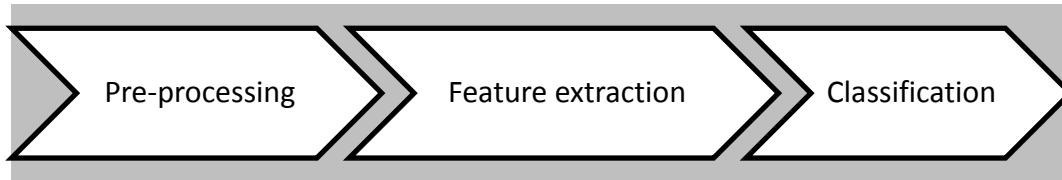


Figure 0-3: General Process of Gait Recognition [28].

Statement of the Problem

Vision-based human identification at a distance in surveillance and security applications has recently attracted more attention by computer vision researchers. Although gait recognition is still a newly used biometric and is not sufficiently mature to be deployed in real world applications, developing the systems that are related to the human identification and specifically through human gait recognition will help to fill in the gaps that need to be completed and to pave the way for the researchers to complete the mission, in this way these systems could be practically used.

Since humans may look like an articulated object, so the joints motion plays essential role in gait recognition which is based on the inclination of the lower limb that is created during walking. The extraction of legs' line is the main problem. This problem arises from the nature of articulated human body and the variant clothes which make it difficult to extract the lines that represent the legs. This problem affects the recognition rate because the extracted line doesn't give the right representation of the body parts. One of the solutions to this problem, in the previous works, is wearing a trouser with a stripe painted on it. However, this is not suitable for identification purposes because of the need of subject contact. Finally, there is a need for a solution that extracts the lines which could achieve high recognition rate without any cooperation or contact with the subject.

Structure of the Thesis

Structure of this thesis is organized as follows. Chapter one presents background information on the current identification and access authentication methods. It also explores traditional methods of recognition and current biometric methods. Finally, it concludes with discussion of the interesting properties and

available modules of the gait recognition based methods. Chapter two presents literature review of the most recent biometric gait recognition methods. In Chapter three, the gait recognition algorithm and the methods used in this work are explored. Chapter four explores the steps involved in designing the proposed gait recognition framework and shows its implementation. Chapter five shows the experimental results and the statistical analysis of performance of proposed framework while Chapter six concludes the thesis with future work.

CHAPTER TWO

Literature Review

Several decades ago, medical studies have shown that gait is a unique signature of humans, all the components the studies considered also point to the viability of gait recognition [40]. This topic has concerned many researches in the last ten years.

Unlike other biometrics, gait biometric has variant factors that affect both gait and gait recognition [26]. This gives a broad range of research in this topic. Next, all works related to gait recognition systems are explored.

Related Work

From a technological perspective, the biometric gait recognition is divided into three groups: Machine Vision (MV) based, Floor Sensor (FS) based, and Wearable Sensor (WS) based as shown in Figure 2-1. In the MV-based approach, gait is captured using a video-camera and then image/video processing techniques are applied to extract gait features for recognition. The primary advantage of MV-based gait biometric is in being captured from distance. In the FS-based approach, gait of the person is captured using sensors (e.g. force plates) installed in the floor whereas in the WS-based category, gait is collected using motion recording sensors attached to various locations on the body of person [16]. In this context, it has to be said that most of the gait recognition methods are MV-based.

As an example of WS-based, Davrondzhon and Einar [15] have demonstrated that the natural arm swing used different technology which is a wearable sensor for non-static parameter that occurs during gait, for unobtrusive user authentication belongs to the WS-based category. Arm movement was collected by using Motion Recording (MR) sensor which is attached to the lower arm of the person.

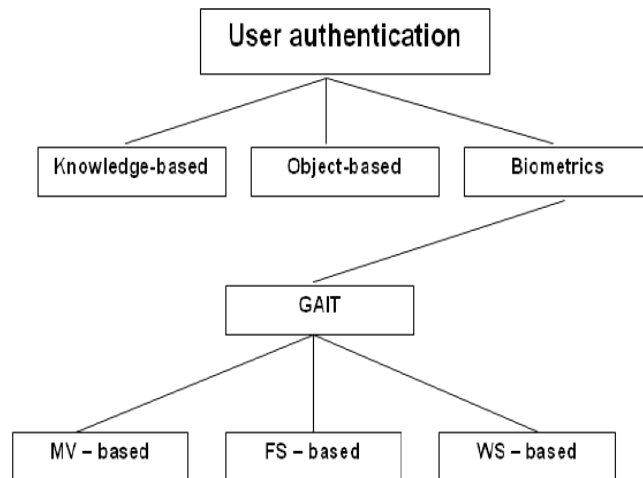


Figure 0-4 : User Authentication Approaches [16].

The MR sensor records acceleration of movement in three directions: up-down, forward-backwards, and sideways. The data set consisted of 120 arm swing samples from 30 persons. Using frequency domain analysis of the arm swing accelerations, an Equal Error Rate of about 10% and identification probability of 71.7% have been obtained. It would be difficult to extract the movement of the arm through machine vision method. Seldom is it to use arm swing as a feature of gait recognition in security domains, but it can be used in medical applications and others.

Jaber and Hadi [25] presented a human gait recognition system based on a leg gesture separation that achieved high precision recognition. Five state of leg in human gait are extracted after background estimation and human detection in the scene as shown in Figure 2-2. Leg gestures are classified over directional chain code of bottom part of silhouette contour. Five spatio-temporal samples were used where their features were applied in Eigen space to five neural networks separately. Performance of each NN for test samples was low (70% to 80%).

Finally after using a neuro-fuzzy combiner classifier for mixing the neural networks for the first time in gait recognition, the result of combination of neural network outputs was satisfactory.

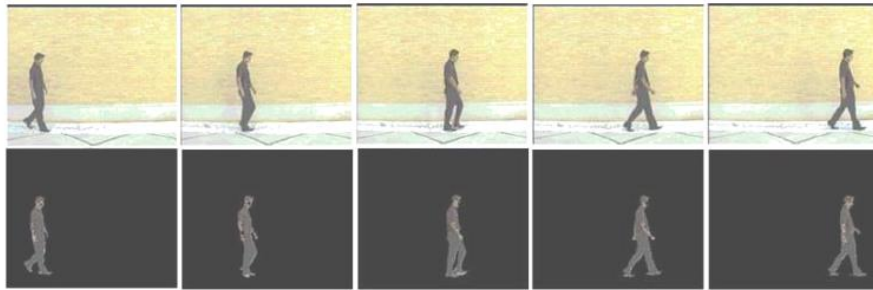


Figure 0-5: Five States of the Leg [25].

Guillen et al. [17] developed a new gait recognition system based on feature subtraction on a bundle rectangle drawn over the observed person as shown in Figure 2-3. The process of analyzing the gait cycle is done through the rectangle's behavior. Background subtraction is achieved using frame difference. After that, Gait features are extracted in aspects such as rectangle's height, width, area, diagonal's angle, and frequency. Through the rectangle's behavior, the parameters that can be concluded are the person height, the change on tiptoe position in the gait cycle and a measure of hands and legs rhythm with their variation. This method resulted in low recognition reliabilities when the features are separately analyzed. However, the system reliability severally increases by analyzing the recognition system as a whole. The reliability of this method is near to 98.6%. The proposed feature extraction main advantage is to reduce the computational cost in the analysis and in the database search time, whereas its main disadvantage that it's difficult to study cases where people are wearing caps or carrying objects such as bags.

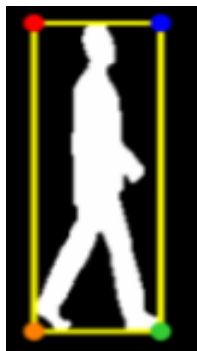


Figure 0-6: Bundle Rectangle [17].

Sharmila et al. proposed a robust method for extracting discriminate gait features automatically and passively [43]. The proposed method extracted four static parameters for person identification. The first two parameters, body height and torso length, characterize the oscillation of the person's height while the other two, leg length and step length, characterize the stride dimensions, viz. the cadence and stride length. In their work, the term 'apparent height' is used to refer to the person's height while walking, which is so called the height variation, as well as it is described as a time-dependent quantity and is different from (though related to) their stature, or standing-height, which is a constant quantity. Because this height variation is an artifact of the walking movement, it is regarded as a gait variable. Significant improvement in identification performance is observed when both height and stride parameters are used rather than when stride parameters only are used. The method is view invariant, works with low-resolution video, and is robust to changes in lighting, clothing and tracking errors.

Different components of human gait are systematically analyzed for the purpose of human identification [36]. Dynamic features such as the swing of the hands/legs, the sway of the upper body and static features like height have been investigated, in both frontal and side views. Starting with dynamic time warping which is a variant of template matching, a more generalized scheme, the HMM was chosen for matching. The matrices of similarity scores between the gait sequences in the gallery and probe sets were computed. As expected, the overall recognition performance improved due to fusion of dynamic and static features. Experiments were conducted on four different datasets.

A visual recognition algorithm was proposed for human identification based on fusion of dynamic and static features of gait [26]. The pose states of the sequence images of the moving person are represented by a sequence of complex vectors. These complex vectors are analyzed by Procrustes shape analysis to obtain the static features of the gait signature. For the dynamic gait information, a condensation framework is used to track the walker and to extract the joint-angle movements of lower limbs. At the end, the static and dynamic gait information are used for

recognition and they are fused on decision level after classification. The experiment has been conducted on 20 subjects, and the results have proved the feasibility of the proposed method.

A new method for gait recognition using dynamic features including the angular measurements of the lower limbs as well as the spatial displacement of the trunk were proposed [22]. Gait signatures are derived using a feature selection algorithm which is based on a validation-criterion. Experimental research is carried out to confirm the early psychological theories claiming that the discriminative features for motion perception and people recognition are embedded in gait kinematics through gait angular measurements.

Cunado et al. control the environment to improve the data collection with a simple, plain background, with controlled lighting as shown in Figure 2-4, [13]. Subjects wore trousers which had a stripe painted on the outside. The video sequences were averaged to reduce high frequency noise and an edge image was produced by employing the Canny operator with hysteresis thresholding. The Hough Transform (HT) is applied to the edge image. Gaps in the data occur when the legs cross where it is difficult to discriminate between the legs. There is also some high frequency noise within the data. To fill in for missing data, and to smooth noisy components, curve fitting was used. These data are then analyzed using the DFT to provide phase and magnitude spectra. The overall classification rate via the phase-weighted magnitude spectra using the k-nearest neighbor rule had considerably better correct classification rate (90%) than using the magnitude data alone (40%).

Bhangale et al. discussed the case when the gait signature is extracted directly from the evidence gathering process [7]. Fourier series is used to describe the motion of the upper leg and apply temporal evidence gathering techniques to extract the moving model from a sequence of images. Enhancing the noise and feature occlusion at extracting temporal features in a sequence of images was achieved by using VHT evidence gathering techniques. The subjects are wearing trousers with the stripe to allow clearer assessment of extraction accuracy. Classification analysis has shown that the phase-weighted Fourier magnitude offered a better classification rate (100%) than just the Fourier magnitude (80%).



Figure 0-7: Walking Subject with Stripe Painted on the Trouser [36].

A model-based moving feature extraction method was used to extract the dynamic motion of the upper leg using temporal evidence gathering technique [5]. Fourier series describes this motion by producing the gait signature. To enhance the accuracy of movement extraction, the subjects wore trousers that have stripes down the middle of the outside of the leg. These stripes enhance the accuracy of extraction.

Aim of the Thesis

Gait recognition systems are still under development and under transition to the practical applications in real life. So, any study in the field of gait recognition is dealing with some aspects of this science because of the many variables in this area, whether these variables was related to the walking person or to the surrounding environment.

The aim of this thesis is to develop a gait recognition system, that achieve a high recognition rate, based on dynamic features by extracting kinetic movement angles for each of the thigh and leg, in an attempt to address shortcoming of previous works. Findings of this study should help researchers in overcoming the challenges they face

CHAPTER THREE

Background Theory of the Thesis

Typical Gait Recognition Algorithm

Figure 3-1 shows a typical gait recognition algorithm [46]. However, steps of each stage may differ from method to another. Firstly, gait must be captured. Gait capturing often falls into two categories, image-based identification and accelerometer-based identification [18]. Image-based approaches recognize the subject from a video of its gait, usually using a surveillance camera. Accelerometer based approaches rely on some type of accelerometer to be placed on the subject to collect data from. While image based approaches are attractive due to the fact that the subject can be identified without requiring the subject to wear a sensor. After gait has been captured, given a gait image sequence, a silhouette for each frame is extracted via background subtraction and noise removal [35]. A series of post-processing is then applied to segment and normalize all frames of each gait sequence [32]. At this point, the frames of gait sequence are ready for feature extraction. Features are classified as static or dynamic features, in essential, static features include the body height, stride and heights of different body parts whilst dynamic features are mainly the Fourier frequencies of motion [23]. Finally the classification and recognition step in which two different approaches exist [10]; template-based classification and classification via machine learning algorithms. In template-based classification, distances between the stored reference and the probe have to be computed. Machine learning algorithms have to be trained during enrolment. The trained classifiers are stored in the database and serve as references.

Background Subtraction

Background subtraction is considered as the basic step in gait recognition especially when the camera is fixed (stationary hypothesis). Most of the MV-based gait recognition algorithms are based on the human silhouette [16].

That is the image background is removed and the silhouette of the person is extracted and analyzed for recognition.

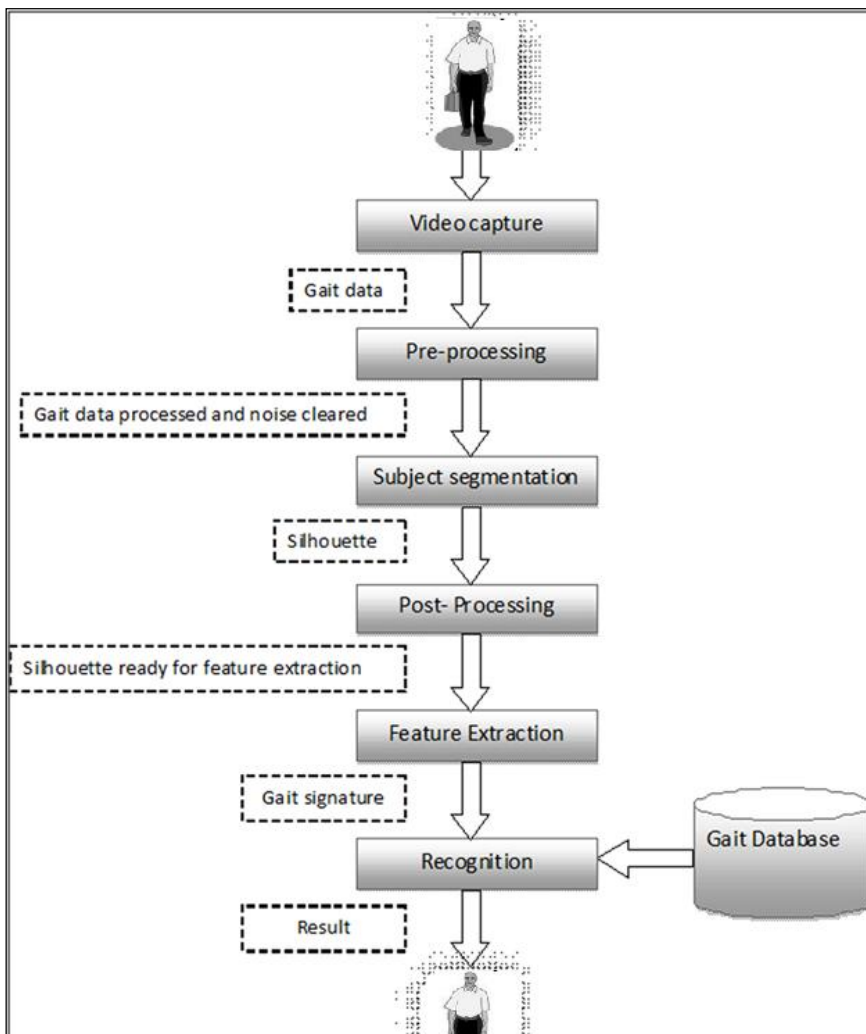


Figure 0-8: A typical Gait Recognition Algorithm [20].

Background subtraction methods subtract the background and keep the foreground subject or the moving subject in order to achieve motion tracking. Motion tracking in digital video aims at deriving the trajectory over time of moving

objects or, in certain cases, the trajectory of the camera. Tracking should be distinguished from object detection that aims at estimating an object's position and/or orientation in a certain image. However, detection and tracking are not totally unrelated [2].

Tracking over time involves matching objects in consecutive frames using some kind of information. Essentially, object tracking methods attempt to identify coherent relations of image information parameters (position, velocity, color, texture, shape, etc.) between frames. Therefore, an alternative classification of object tracking algorithms can be based on the type of information they employ for matching [2].

Frame Difference

In this simple technique, the background subtraction is achieved with two images of the same person delayed from each other. The absolute difference between the two images is threshold where the brightness threshold θ in an image is chosen as shown in Figure 3-2, [17].

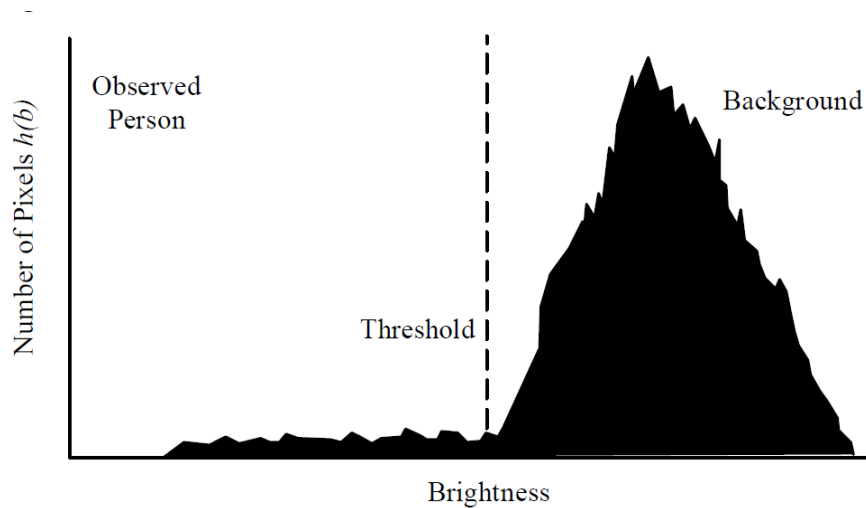


Figure 0-10: Image Brightness Histogram [28].

This approach works as follow: if the image pixel is greater than the threshold, then the image pixel is considered part of the foreground, else the image pixel is considered part of the background.

The pixel-wise difference between two or three consecutive frames in video imagery, to extract moving regions, is referred as temporal differencing. The main drawback of temporal differencing is that it fails to extract all relevant pixels of a foreground object especially when the object has uniform texture or moves slowly [29]. However, it is useful only in dynamic environments because as soon as an object stopped moving, it will be considered as background entity. Also, it is unable to extract the complete shape of moving objects [21].

Temporal Median Filter

It is also called the approximate median. In this technique, the last n frames of video are used as a buffer to calculate the background model by computing the median value of the buffered frames [39]. If a pixel in the current frame has a value larger than the corresponding background pixel, then the background pixel is incremented by 1, else the background pixel is decremented by 1.

Median-Filter approach requires memory and it is associated with cost due to buffering the recent pixel values. Another disadvantage of this approach is considering the noise and some fast objects as foreground objects. On the other hand, Temporal Median Filter provides stability of the background model [11].

Running Gaussian Average

At each pixel value, the running Gaussian average models the background by computing the Gaussian probability function at each new frame per Equation 1, [39].

$$\mu_t = \alpha I_t + (1 - \alpha)\mu_{t-1} \quad (1)$$

Where I_t is the pixel's value, μ_t is the previous average, and α is the empirical weight. The decision rule of this technique works as follow: the pixel can be classified as foreground pixel if the inequality is achieved per Equation 2. Otherwise, the pixel will be classified as background pixel.

$$|I_t - \mu_t| > k \sigma_t \quad (2)$$

The main advantage of this technique is the low speed because of the low memory requirement.

Mixture of Gaussian (MoG)

Rather than explicitly modeling the values of all the pixels as one particular type of distribution, we simply model the values of a particular pixel as a mixture of Gaussians. Based on the persistence and the variance of each of the Gaussians of the mixture, we determine which Gaussians may correspond to background objects. Pixel values that do not fit the background distributions are considered foreground until there is a Gaussian that includes them with sufficient and consistent evidence supporting it [44].

This approach consists of modeling each pixel as a mixture of Gaussians and using an on-line approximation for updating the model. This method showed a substantial progress to handle complex scenes, separating out objects and robust at suppressing background noise. Therefore, until nowadays, GMM-based background subtraction is considered as a standard method and it has become the basis for a large number of related methods [9].

Hough Transform

Hough transform is a well-known clustering technique where the data samples vote for the most representative feature values in a parameter space [2]. The practical function of Hough transform is to find lines, circles or any other curves in an image. However, the simplest Hough transform is the Hough line transform which produces efficient procedure for detecting lines in an image [41].

There are two kinds of Hough line transform; the Standard Hough Transform (SHT) and the progressive probabilistic Hough Transform (PPHT). A binary image is used as an input where each active pixel represents part of an edge feature. The standard Hough transform maps each of the pixels to many points in the parameter space [8]. In the case of line detection, a single edge pixel is mapped to a sinusoid in 2D parameter space (θ, ρ) per Equation 3.

$$x \cos \theta + y \sin \theta = \rho \quad (3)$$

All possible lines that pass through that image point (see Figure 3-3) are presented via an accumulator to get parameter for the detected lines. This process is referred as voting, where the points in an image evaluate to sinusoids in a parameter space, and the points in parameter space evaluate lines in an image.

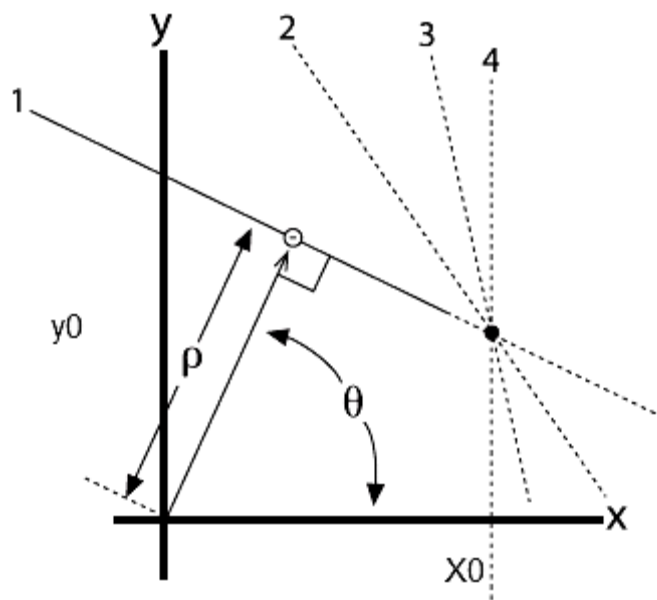


Figure 0-11: Many Lines Parameterize by a different ρ and θ [8].

The accumulator is a two dimensional array where the rows and columns represent (θ, ρ) , respectively. By equation (3), lines in the image will be obtained through finding the values of (θ, ρ) , where the accumulator cell is a local maxima.

Unlike the standard Hough transform where the transform is performed on a pre-selected fraction of input points, progressive probabilistic minimizes the amount of computation needed to detect lines by exploiting the difference in the fraction of votes needed to reliably detect lines with different numbers of supporting points [24]. Using these gradient information where accumulating would also speed up the voting process, and serve to reduce further that clutter in the accumulator space.

Discrete Fourier Transform (DFT)

A signal can be analyzed either in the time (or spatial) domain or in the frequency domain [14]. Fourier analysis is a family of mathematical tools that convert the signal from time domain to frequency domain and vice versa. The Discrete Fourier Transform (DFT) is particularly used with digital signals [45].

The input signal is assumed to be in the time domain. The most common type of signal entering the DFT is composed of samples taken at regular intervals of time. Of course, any kind of sampled data can be fed into the DFT, regardless of how it was acquired. The term frequency domain is used to describe the amplitudes of the sine and cosine waves as shown in Figure 3-4. The frequency domain contains exactly the same information as the time domain just in a different form [14].

The Fourier transform process decomposes the signal into sinusoids and depending on the property of sinusoidal fidelity, a sinusoidal input to a system is guaranteed to produce a sinusoidal output [45]. After the signal has been transformed, only the amplitude and the phase could be changed. These changes give the characteristics of the system. Therefore, the frequency domain tells us the behavior of the signal, in other words it describes how the signal changes is.

The analysis equations for calculating the DFT is done by correlating the input signal with each basis function as shown in Equations 4 and 5.

$$ImX[k] = - \sum_{i=0}^{N-1} x[i] \sin\left(\frac{2\pi ki}{N}\right) \quad (4)$$

$$ReX[k] = \sum_{i=0}^{N-1} x[i] \cos\left(\frac{2\pi ki}{N}\right) \quad (5)$$

where $x[i]$ is the time domain signal being analyzed and $ReX[k]$ and $ImX[k]$ are the frequency domain signals being calculated. The index i runs from 0 to $N-1$ while the index k runs from 0 to $N/2$ [45].

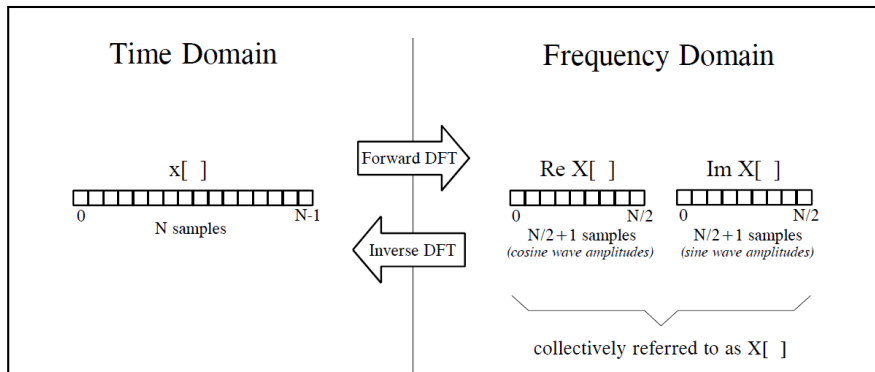


Figure 0-12: Forward and Inverse DFT [9].

Classification Techniques

Pattern recognition aims at classifying items into different classes of groups, as shown in Figure 3-5, based on the application used [42]. The items that form the pattern can be numbers, images, signals or any type of measurements.

Depending on the mechanism of action, there are different classification approaches [31]. The first one is the template matching method which is based on the concept of similarity where the difference distances are computed. The second approach is based on Bayes decision rule, the maximum likelihood, or density estimator. The three well known methods are K-Nearest Neighbor, Parzen Window classifier, and Branch-and-Band methods. The third approach is based on building the decision boundaries by correcting the error criterion. Neural networks and support vector machine are the most important methods representing this approach.

Next, a summary of the most important methods is presented.

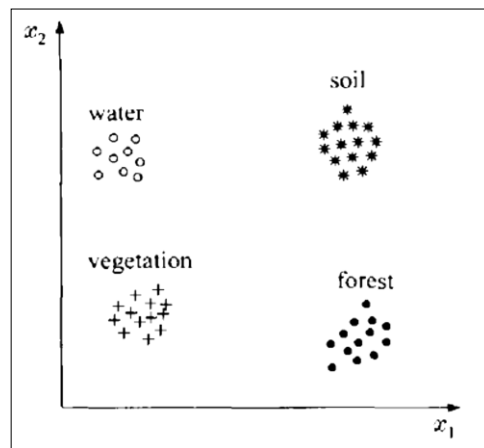


Figure 0-13: Classification of Various Types of Ground Imaging [42].

Neural Networks

A well-known technique based on the notion of perceptron. Single layer network treats a linear separable data. On the other hand, multilayer neural networks, consist of number of neurons joined together in a pattern of connection, are used to solve nonlinear problems [42].

The process of artificial neural network classifier depends on the input, the activation rule of the units (neurons), and the weight of each connection. The weights are updated repeatedly in the training phase until reaching stability. For classification, the new test pattern is placed at input unit's layer [30]. The calculation of this new input with the final values of weights is performed to get the output values that have to be closer to the desired ones. In ANN [30], a large sample size is required to obtain satisfied accuracy. Also the variations in the features make the training of the network impractical, Thereupon; the weights of the network will not approach to the optimal values.

Decision Tree

It is a predictive machine learning method capable of modeling nonlinear system features. In tree-based algorithm, different levels of the tree represent different feature classes [42]. However, an improvement has taken place by changing the shape of the feature class (e.g. hyper planes or hyper rectangles) which is important to raise the accuracy of the future prediction.

In the tree based classification, the decision classifier fires sequentially in multistage until we reach finally to the target class. It has good performance on complex nonlinear data but it is time consuming in the training phase [4].

Naïve Bayes

It is the basic approach of Bayesian network, as shown in Figure 3-6, where the Bayesian network consists of two type of information [33]. The first one is the node structure of the features that represent the problem domain and the connections between these feature variables. Whereas the second one is a quantity information representing the probability distribution functions of the connection between variables.

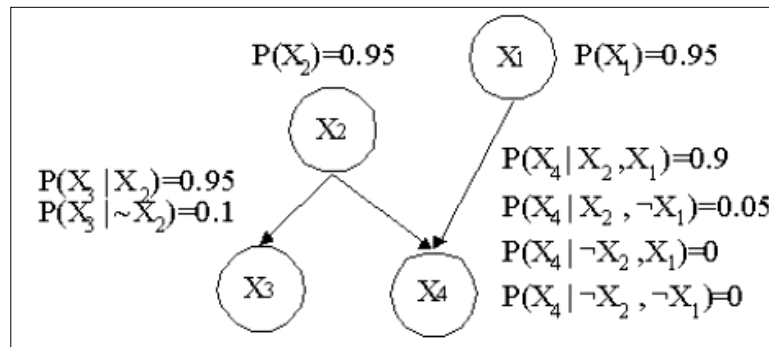


Figure 0-14: The Structure of a Bayes Network [33].

The Naïve Bayes is a probabilistic learning classifier described by directed graphs, where each node in the graph has one parent [30]. The variables are independent so the existence of any feature does not rely on the existence or the absence of any other feature. The following equation represents the Naïve Bayes theorem:

$$P(h \setminus D) = \frac{P(D \setminus h) P(h)}{P(D)} \quad (6)$$

where $P(h)$ is the a prior probability of independent hypothesis instance and $P(D)$ is an independent probability of the data D .

The independency in this method makes it time effective for training. Another advantage of this method is the need for a small size of data to specify the parameters. A review of classification techniques describes Naïve Bayes classifier as it usually has less accuracy than other sophisticated techniques [30].

Support Vector Machine

It is supervised learning method where the pattern vectors are mapped to a high dimensional feature space. Hyper planes are constructed to separate the feature space [4]. The items of patterns are represented as points in space [42], so, the classification will be through separating the space by gaps between the categories. A new input will be mapped into the same space to predict the category that belongs to.

On the other hand, support vector machine is capable of classifying linear and nonlinear sets of data [31]. It has good performance and it can train generalizable nonlinear classifiers in high dimensional space using a small training set. From another side, the discrete data presents a problem because support vector classifier is related to the binary classification.

K-Nearest Neighbor

A K-nearest-neighbor method is considered as a nonparametric method of density estimation. It provides class-conditional density estimates. The k-nearest-neighbor approach works by fixing the probability, $k=n$, or equivalently, for a given number of samples n , to fix k , and to determine the volume V which contains k samples centered on the point x [4]. One of the parameters to choose is the value of k . If it is too large, then the estimate will be smoothed and fine detail averaged out. If it is too small, then the probability density estimate is likely to be spiky because of that more samples will be plotted. Thus, the decision rule is to assign a new x to the class that receives the largest vote amongst the k -nearest neighbors.

Among the classification techniques, k-nearest neighbor gives a low classification error and is adopted in many applications [1]. It is considered a simple robust method and it is recommended to implement KNN as a baseline classification technique [4].

CHAPTER FOUR

Gait Recognition Design and Implementation

System Design

This section presents the design of the proposed gait recognition framework. Figure 4-1 shows an overview of the system design.

To recognize a person using the extracted features from the video stream, proposed gait recognition framework must consist of training and testing phases. The training phase is performed first in order to train the system to provide clustering of unknown data. After training phase has finished, testing is performed every time a new sample is obtained for recognition. In the training phase, the gait signature is stored in the database while in the testing phase; the gait signature is passed to the classifier.

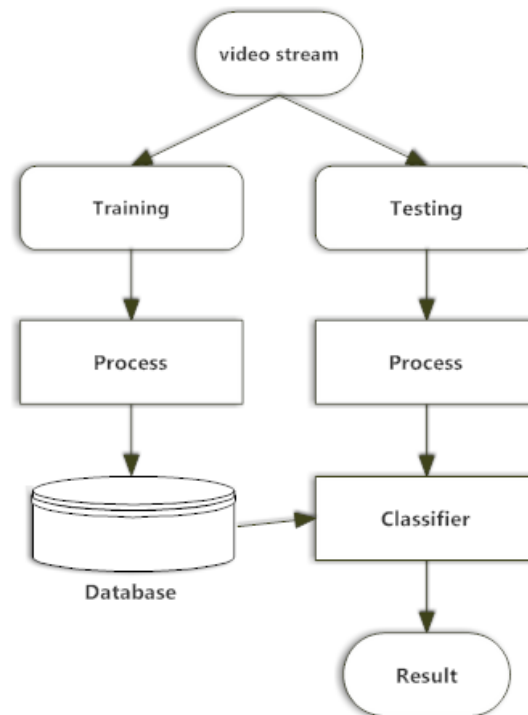


Figure 0-1: Overview of System Design.

The proposed gait recognition framework consists of two stages. Figure 4-2 shows the first stage of the proposed framework which uses Mixture of Gaussian algorithm to subtract the background scene and detect the foreground. After that, post-processing is performed by finding the connected contour of the walking person. Finally, through that contour, a computation of the gait cycle is accomplished via using the stride width manner to supply the beginning and the end of the gait cycle.

The second stage, as shown in Figure 4-3, is applied on the extracted region from each video frame that marks beginning and end of gait region. This stage includes processing each frame through obtaining the body skeleton of the walking person. After that, Hough Line Transform is used to mark straight lines from the body skeleton. These lines are filtered by the proposed Filter Lines Algorithm to extract the lines that are used in extracting the gait signature.

By employing the slopes of thigh and leg, the dynamic changes of the person inclination are transformed to frequency domain via Fourier Transform to produce a discriminative representation of gait signature. Finally, the extracted features of gait are fed to k-nearest neighbor classifier for the final decision.

Gait Recognition Framework Implementation

In this section, implementation of the proposed gait recognition framework is presented. The implementation includes work environment and the two-stage processing of each video frame as shown in Figures 4-2 and 4-3.

First of all, the environment used to develop the proposed gait recognition framework is Microsoft Visual Studio 2008 with OpenCv library.

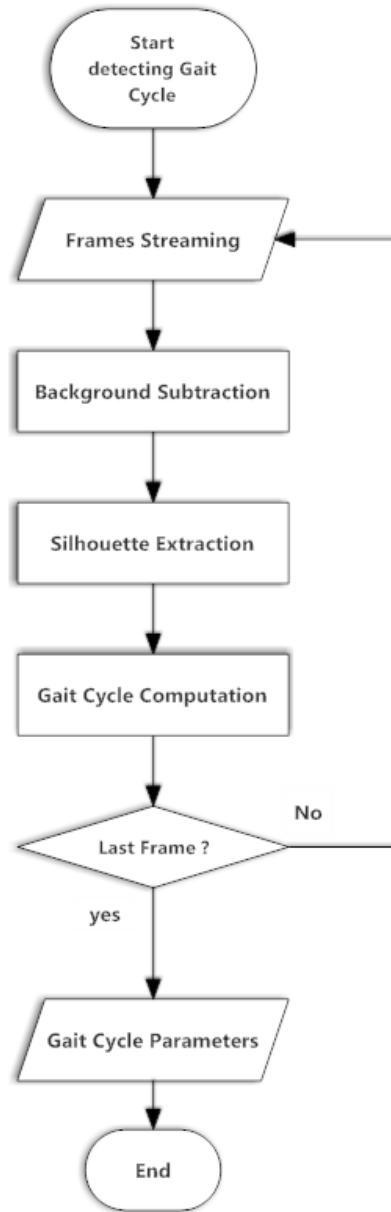


Figure 0-2: First Phase of Gait Recognition Framework.

OpenCv Library

OpenCV (Open Source Computer Vision) is a library consists of programming functions intended for real time computer vision. OpenCV is available free for both academic and commercial use. It has C++, C, Python, and soon Java interfaces running on Windows, Linux, Android, and Mac. The library can be categorized into five main components, four of which are shown in Figure 4-4. The

CV component includes basic image processing and higher-level computer vision algorithms. The ML component is the machine learning library that includes different statistical classifiers and clustering tools. The HighGUI component provides I/O routines and functions for storing and loading videos and images. The CXCore component contains basic data structures. The CvAux component provides face recognition modules and background/foreground segmentation modules [19].

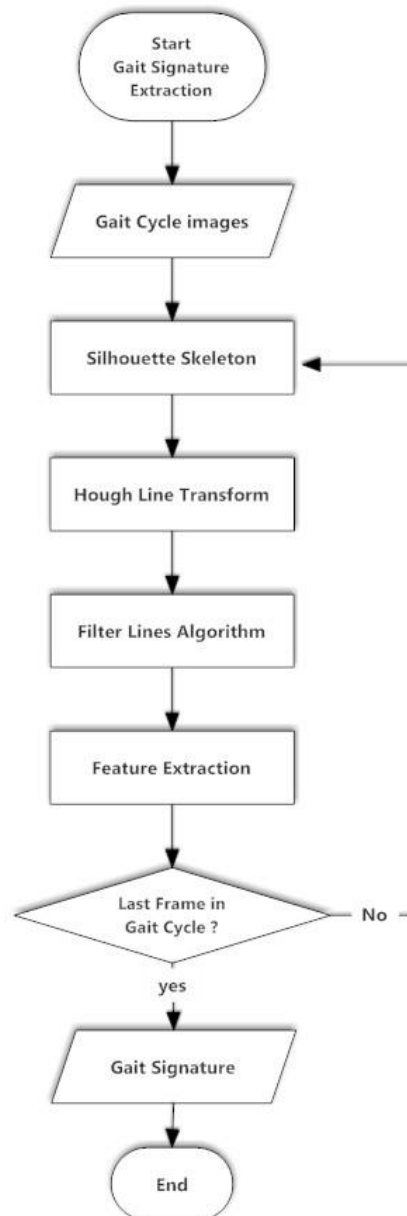


Figure 0-3: Second Phase of Gait Recognition Framework.

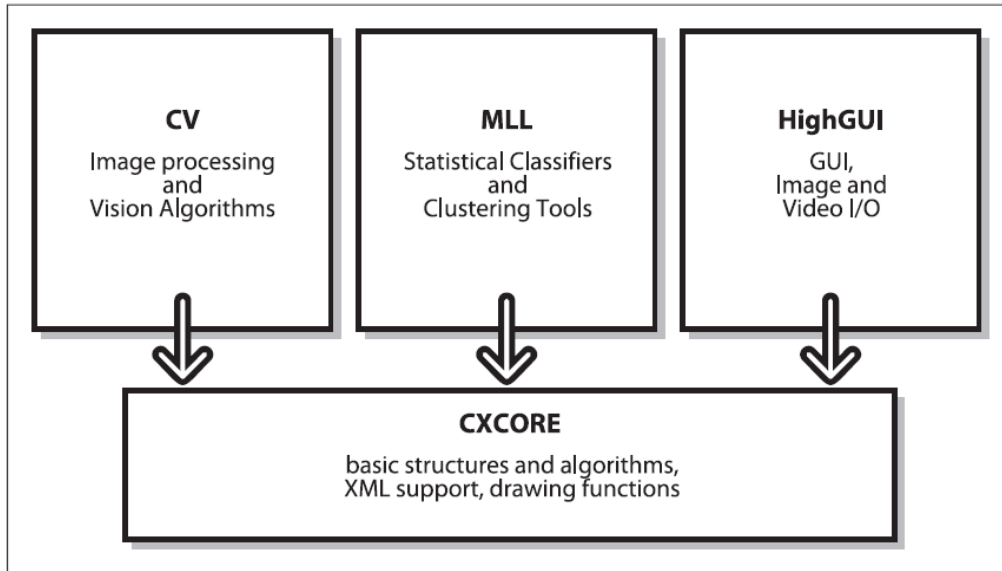


Figure 0-4: The Basic Structure of OpenCV Library [19].

Data Preprocessing

As a preprocessing, background subtraction is performed. The background subtraction is applied using mixture of Gaussian method. Then, the resulted image is enhanced to remove the noise and to extract the connected components of silhouette. In this thesis, video is treated as a sequence of images.

Background Subtraction

To extract the gait signature, the silhouette is extracted through subtracting the background leaving the foreground walking subject. The background subtraction is implemented using the Mixture of Gaussian. Each pixel in the scene is modeled by a mixture of K Gaussian distributions. The probability that a certain pixel has a value of X_N at time N can be written according to equation 1.

$$p(X_N) = \sum_{j=0}^k w_j \eta(X_N; \theta_j) \quad (1)$$

where the w_j represents the weight parameter of the k^{th} Gaussian component and $\eta(X; \theta_k)$ is the Normal distribution of k^{th} component.

Each Gaussian associated with a pixel is given a weight based on how many samples a specific pixel has contributed to the specific Gaussian. This weight is updated at each frame of sequence as shown in Figure 4-5. The window size parameter is used to control the learning rate which set to $\alpha = \frac{1}{\text{win size}}$.

For a test pixel to be classified as background, it must be not further away than one standard threshold from a specific Gaussian. When a pixel is tested to see if it belongs to the background, it is checked against only the Gaussians that contribute to total of the background threshold of 0.7. Finally, to reduce noise as areas of connected pixels the minimum are is set to 15 pixels. This indicates that any total number of pixels less than the minimum area is not considered as foreground subject.

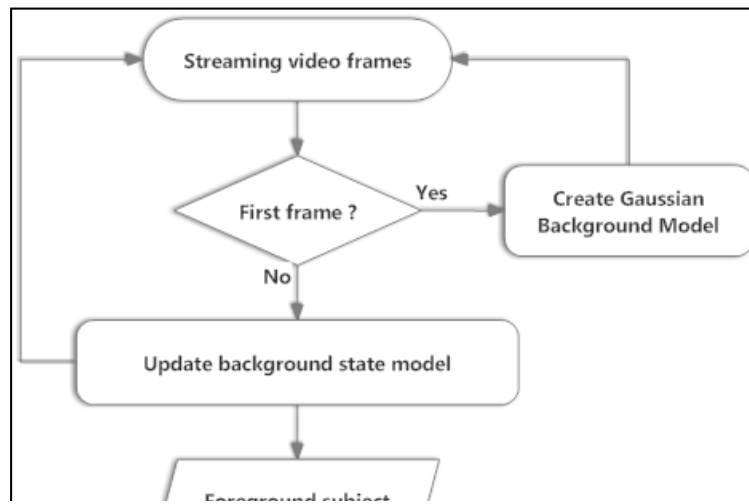


Figure 0-5: Illustration of background subtraction using MoG.

Silhouette Extraction

After background subtraction, the output image may contain noise resulted from surrounding variants like lightening changes or small subjects movements. Therefore, a pruning procedure is used to remove any noise in the image and to extract only the silhouette of a walking person.

Firstly, to remove the small-size noise and clean up the noisy foreground image, the morphological operations erosion and dilation are used. In this step, a region of the image is convoluted with a kernel of size 3x3 pixels with the anchor at its center to avoid any distortion to the original image. The impact of the erosion is the same as that of a local minimum operator used to eliminate the noise as shown in equation 2. The dilation makes an effect of that of a local maximum operator used to find the connected component through patching the regions lost in erosion according to equation 3.

$$erode(x, y) = \min_{(x', y') \in kernel} src(x + x', y + y') \quad (2)$$

$$dilate(x, y) = \max_{(x', y') \in kernel} src(x + x', y + y') \quad (3)$$

The resultant image is expected to have remains encapsulated into contours or blobs. These contours are approximated by polygons in order to toss out the undesired small components.

Gait Cycle Detection

After the silhouette of the subject is extracted and utilizing from the principle of periodicity of the gait, the gait cycle is detected based on stride width. The steps that have been taken to calculate the stride width are summarized as follows:

- Set the lower part of legs as a region of interest.
- Approximate this lower part by convex hull.
- Mark this part using a box.
- Find width of the marked box, this width is calculated for each frame and saved in an array.

If we assume the walking cycle starts when the right leg in front and the left leg in the back, distance between both legs is maximized and we call it the maximum width. At the middle of the walking cycle, we have another maximum width when the left leg in front and the right leg in the back. At the end of the walking cycle, we have another maximum width when the right leg in front and the left leg in back.

This indicates that during a walking cycle, we have three maximum width states. To extract one walking cycle from a video frame, we look for three maximum width states.

In practice, the procedure of determining one gait cycle is passed through the stride maximum width three times. For example, if the gait cycle is started at the first maximum width, the end of gait cycle will be at the third maximum width. Similarly, when we start the gait cycle at the second maximum width, the end of gait cycle will be at the fourth maximum width. Sometimes the stride maximum width could be a little confused, as it shown in Figure 4-6, where the peak at T2 is the point of the real maximum width while the peak at T1 is taken place because of the foot shadow. To overcome this problem, the width of the stride is calculated at each frame of the corresponding video and saved in an array. By passing a loop on this array, if the width in the current frame is greater than that in the previous frame, then the counter of the rise state, this counter counts the states when the stride width in the current frame is greater than it for the previous frame, is incremented and the counter of the down state, this counter counts the states when the stride width in the current frame is smaller than it for the previous frame, is reset, else the counter of the down state is incremented. After that, at each step of the loop, booth of the rise state counter and down state counter is tested. If they are greater than 3, then the current width is considered as a maximum width and the counters are reset.

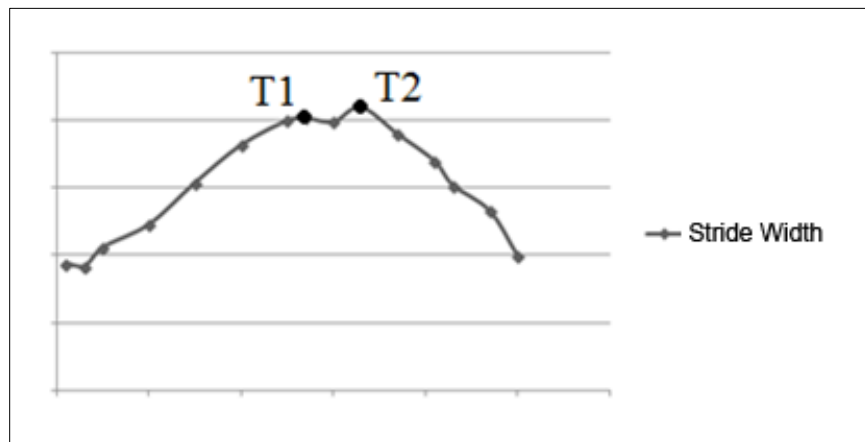


Figure 0-6: Determining Stride Width.

Hough Line Transform

In this stage, the skeleton is extracted from the obtained silhouette. A set of morphological operations (erosion and dilation) are used for this purpose. These operations are repeated iteratively until the maximum locations are equal to zero. After obtaining the skeleton for each frame, Hough Transform is used to produce an image that contains lines representing the body parts. The equation 4 is used to obtain lines.

$$\rho = x \cos\theta + y \sin\theta \quad (4)$$

There are some parameters in Hough Transform that we can control to get more optimal results, these parameters are:

- The minimum line length retrieved.
- The maximum gap between line segments lying on the same line to treat them as a single line segment (i.e. to join them).
- Threshold parameter: a line is returned by the function if the corresponding accumulator value is greater than the predetermined threshold.
- Rho: Distance resolution measured in pixels.
- Theta: Angle resolution measured in radians.

Filter Lines Algorithm

Filter Lines Algorithm (FLA) is proposed in this work to select the lines that represent the thigh and leg. The proposed FLA can be summarized as follows. First, each produced line, from Hough Transform, holds the x – *and* y – values of the start and endpoints. The slope of each line is calculated according to the following formula.

$$s = \frac{y_2 - y_1}{x_2 - x_1} \quad (5)$$

Then, the following distance formula is used to compute height of each line.

$$tall = \sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2} \quad (6)$$

At this stage, we have the starting point and the end point of each line in the frame and the slope and height of each line. All these parameters are saved in a temporary matrix just within the process of each frame as shown in table 4-1.

Table 0-1: Extracted Line Properties.

x_0	y_0	x_1	y_1	S	T
Start-point	Start-point	End-point	End-point	Slope	Tall

where x_0 represents the x-value of the starting point which forms the lower value and x_1 is the x-value of the ending point which forms the higher value.

In order to reduce the computational cost, lines that are related approximately to the upper part of the body are discarded. This is done through calculating height of the walking subject and truncating the upper half of the walking subject. The following two equations are used.

(7) The height of the body = high y – low y

(8) The lower body part value = high y – (0.5 * height)

Another challenge rises at this stage. After the walking subject is converted into its skeleton and then transformed via Hough Transform, it may produce extra lines that do not represent body parts as shown in Figure 4-7.

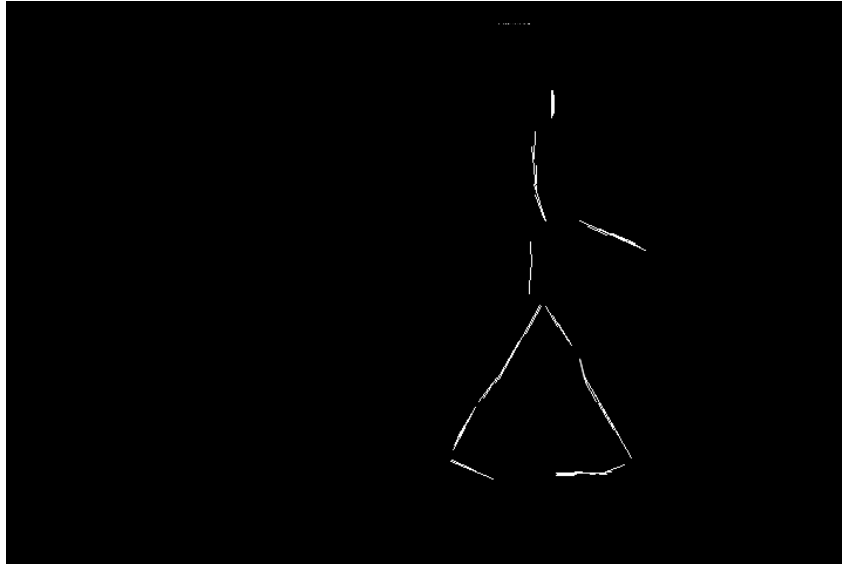


Figure 0-7: Extra Lines that need to be eliminated.

As mentioned before, each line extracted by Hough Transform has the properties listed in table 4-1. Before the Hough Transform step, the frame is divided into grid of pixels 720 X 480 as illustrated in Figure 4-8.

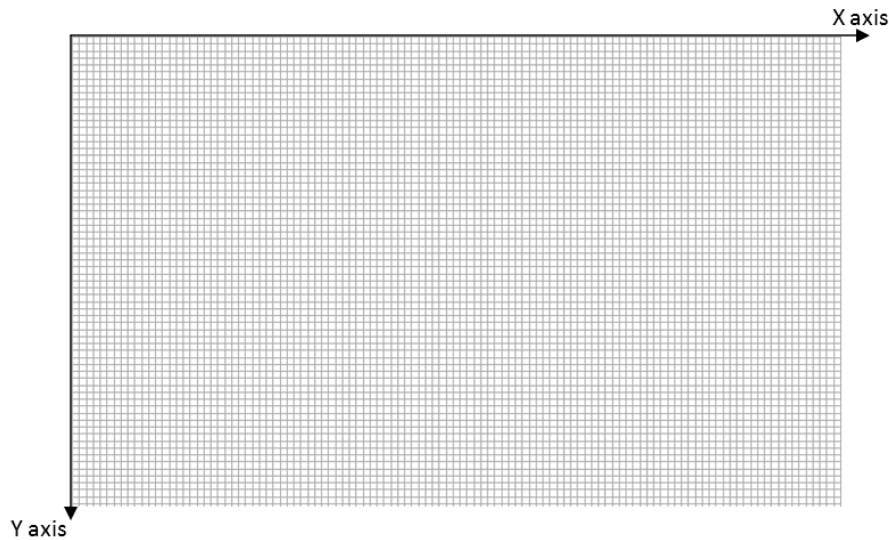


Figure 0-8: Grid of Pixels.

Referring to Table 4-1, y_0 and y_1 are undetermined. It is unknown which of one of them represents the starting point and which one represents the ending point and which one of them has the lower or the higher value. However, they can be determined depending on the slope value, if the slope value is positive then y_0 is the starting point which has the lower value, and y_1 is the ending point which has the higher value, and vice versa if the slope is negative.

In summary, the proposed Filter Lines Algorithm is used to filter out the extra lines resulted after taking the Hough Transform of the skeleton body. The proposed algorithm is based on the structure shape of the human body. It depends mainly in its solution on the line slope and the height of line. The algorithm is divided into five sub filters as illustrated in Figure 4-9.

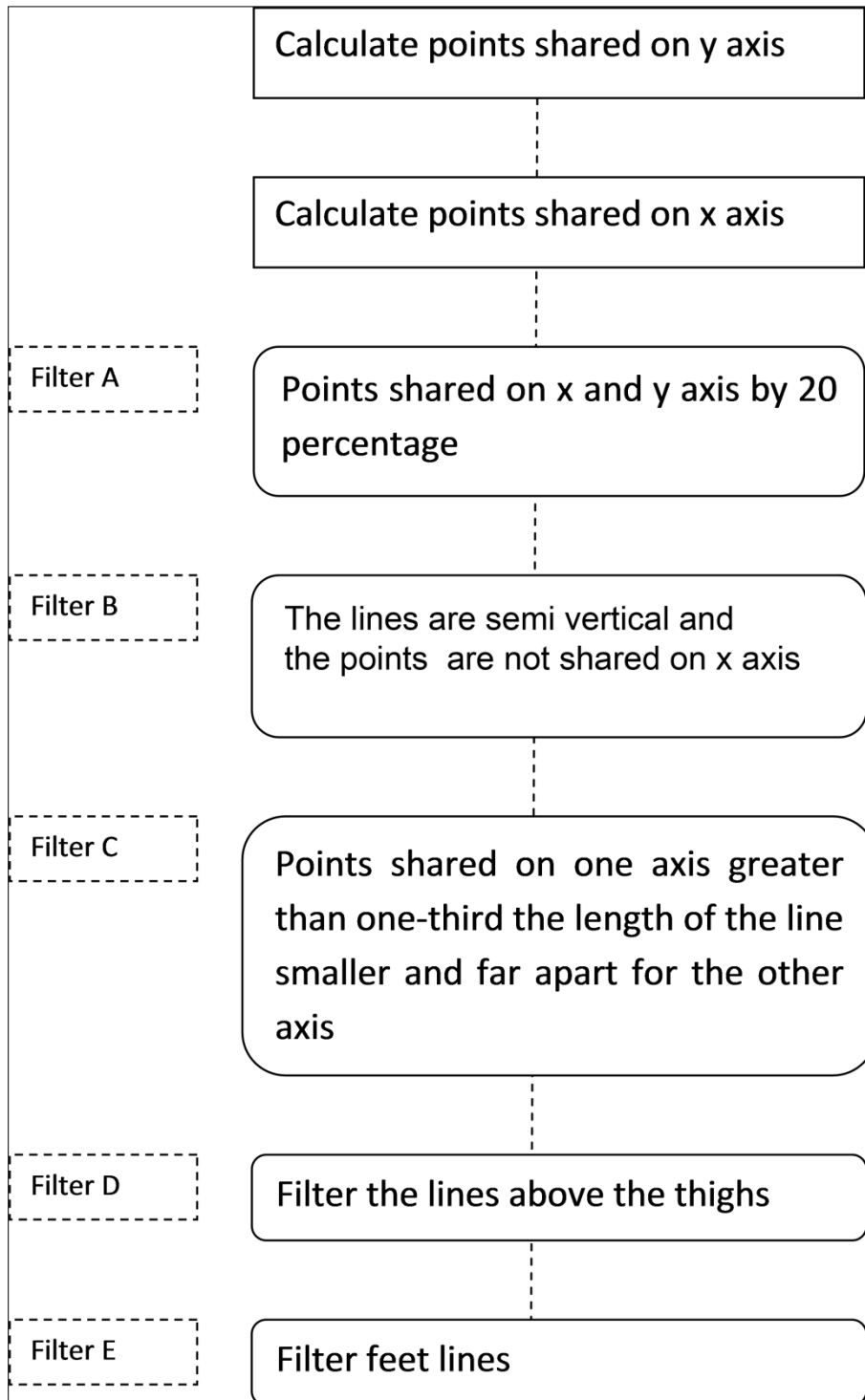


Figure 0-9: Flowchart of Filter Lines Algorithm.

Figure 4-10 shows the flow chart of the algorithm used to find the points shared on y axis. The shared points on y axis are the common points on the projection of the two lines on y axis.

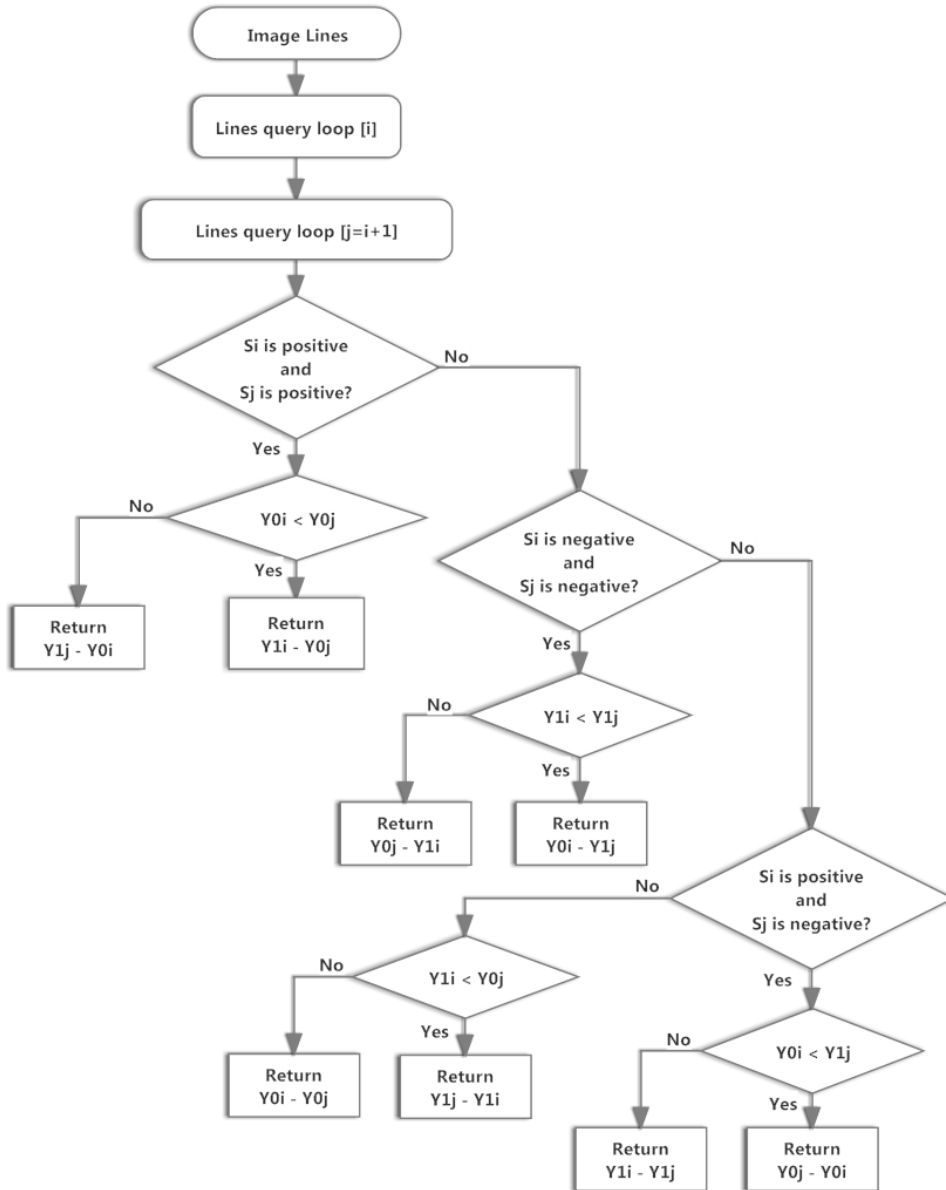


Figure 0-10: First Phase of Filter Lines Algorithm.

Figure 4-11 shows the algorithm used to find the shared points on x axis. These are the points common on the projection of the two lines on x axis. Figure 4-12 illustrates how the two algorithms work.

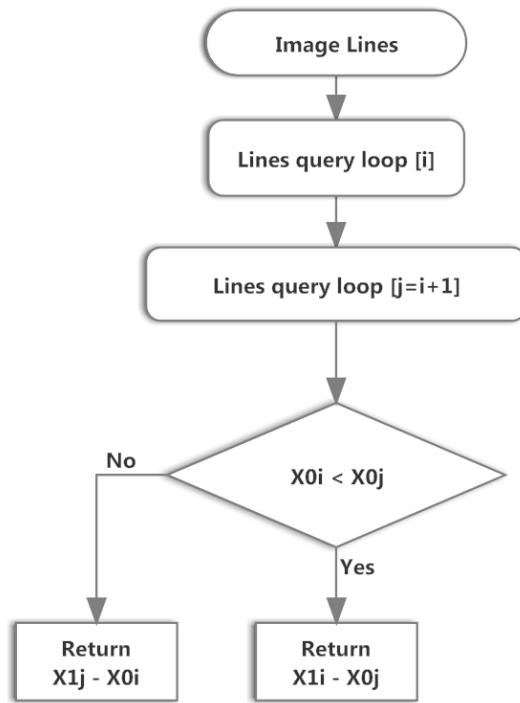


Figure 0-11: Second Phase of Filter Lines Algorithm.

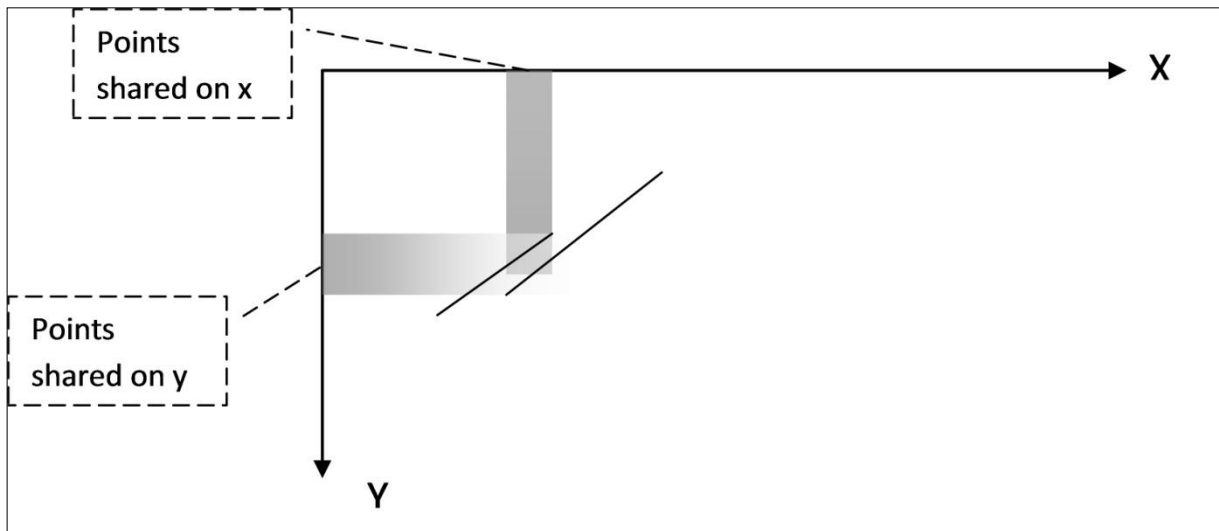


Figure 0-12: Example of Shared Points on x Axis and y Axis.

As Figure 4-13 shows, after cutting the upper part of body, the remaining lines are the lines of the lower part of body. As the figure indicates, the lines which have a slope value with difference value between zero and one could be resulted from the same body part. It is found by experimental analysis that if the two lines have a slope value with difference value between zero and one, they have points shared on y axis with value of 20 percent of the smaller one tall at minimum, and they have points shared on x axis with value of 20 percent of the smaller one tall at minimum, then the two lines resulted from the same body part. In this way, Filter A is used to remove the smaller lines.

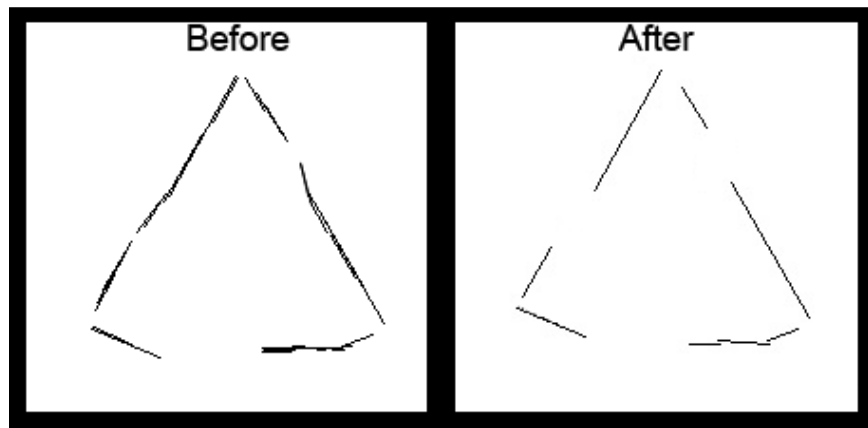


Figure 0-13: Illustration of Filter A.

Filter B deals with the case when the two lines have the same slope value and have shared points on y axis with higher value of pixels whilst not shared on x axis, but at the same time, the two lines almost vertical and represent the same part of the lower body part as shown in Figure 4-14. The proposed criterion is to test the verticality. A variable called *ver* is defined per Equation 9.

$$ver = \frac{(|x_{0i} - x_{0j}| + |x_{1i} - x_{1j}|)}{2} \quad (9)$$

where *i* represents the index of the first line and *j* represents the index of the second line. Therefore, if the variable *ver* is less than 4, then the lines are almost vertical. Consequently, Filter B removes the smaller line.

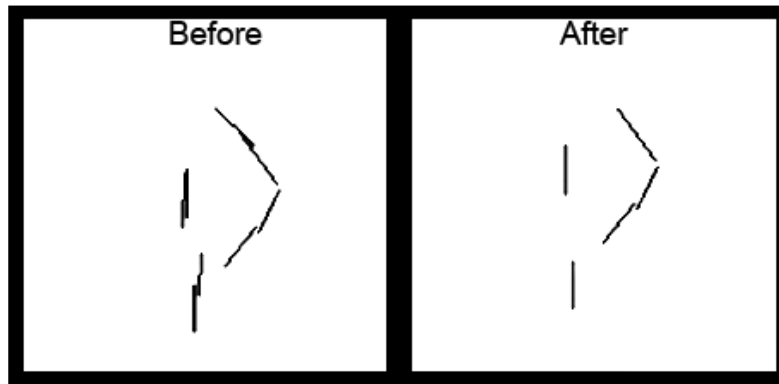


Figure 0-14: Illustration of Filter B.

Filter C deals with another problem of unexpected lines which is different from the preceding problems as illustrated in Figure 4-15.

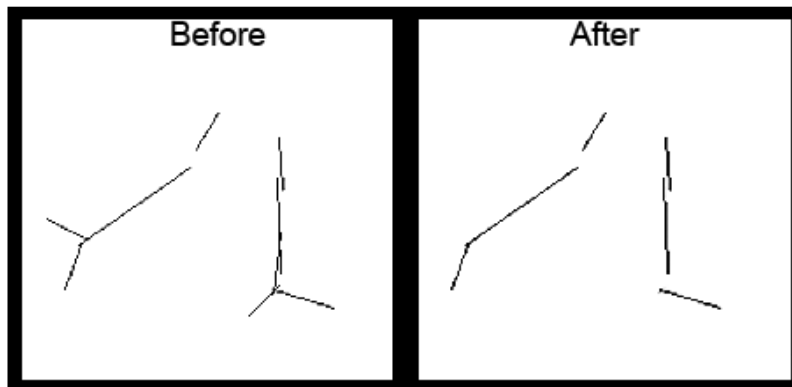


Figure 0-15: Illustration of Filter C.

Filter C works as follows. The lines are sorted in an ascending order with respect to x_0 . Two successive algorithms are applied as shown in Figure 4-16. The test is applied on each successive lines and the comparison is performed with respect to the smaller line. If the points shared on one axis are greater than one-third the length of the smaller line and at the same time the points shared on the other axis is greater than (-2) which means that the projection of the two lines on the other axis may be separated by 2 points, Filter C removes the smaller line.

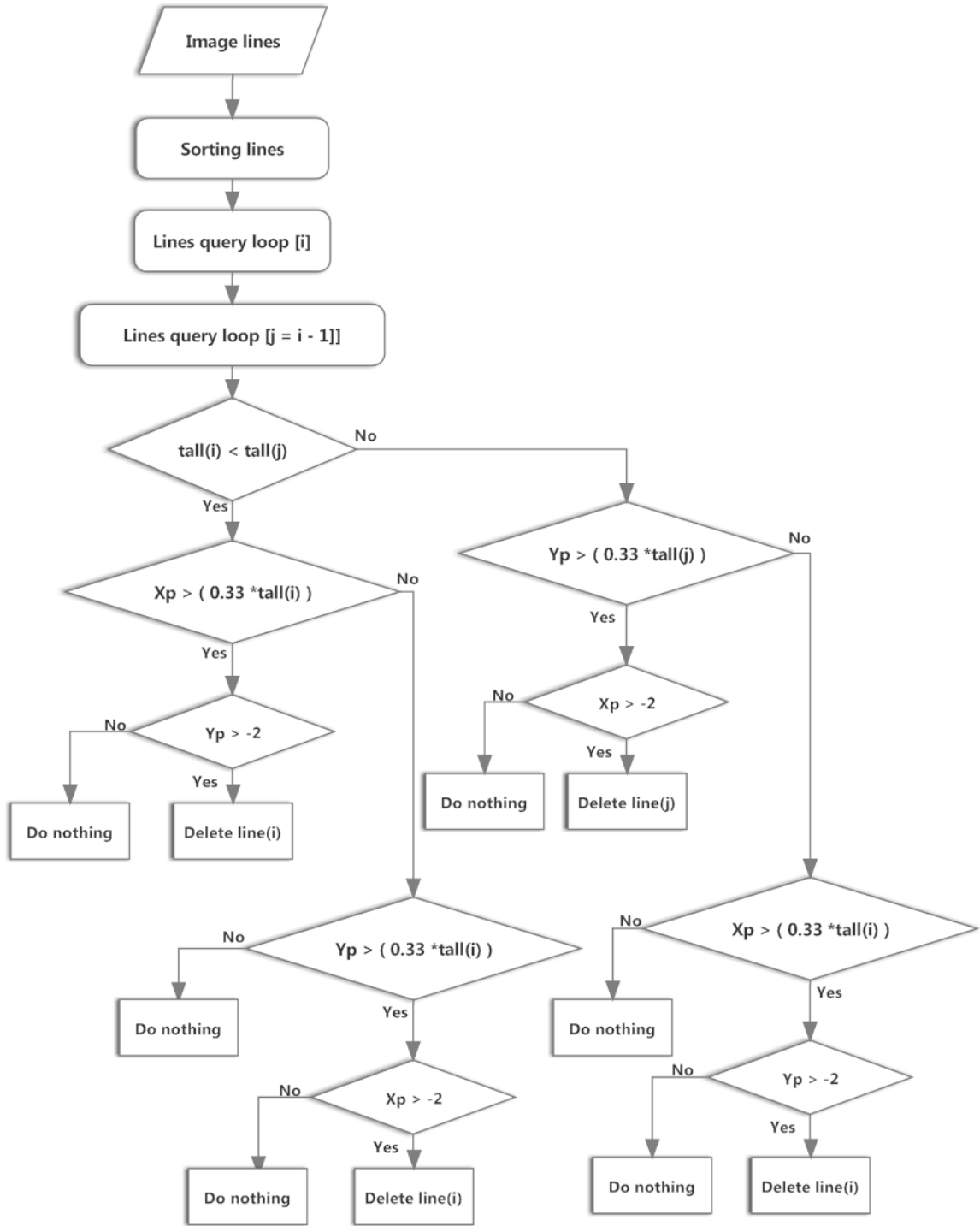


Figure 0-16: Flow chart of Filter C.

After cutting off the lower part of the body, we have to make sure that there are no lines above the thigh lines. Filter D recognizes thigh lines and filter out lines above the thigh and at the same time, finds the middle point that divides the lines of lower body part into front and back. Studying nature of human shape, the lines of thigh have some properties as shown in Figure 4-17:

- $x_{21} > x_{11}$
- The slopes have different sign.
- The two lines have shared points on y-axis.

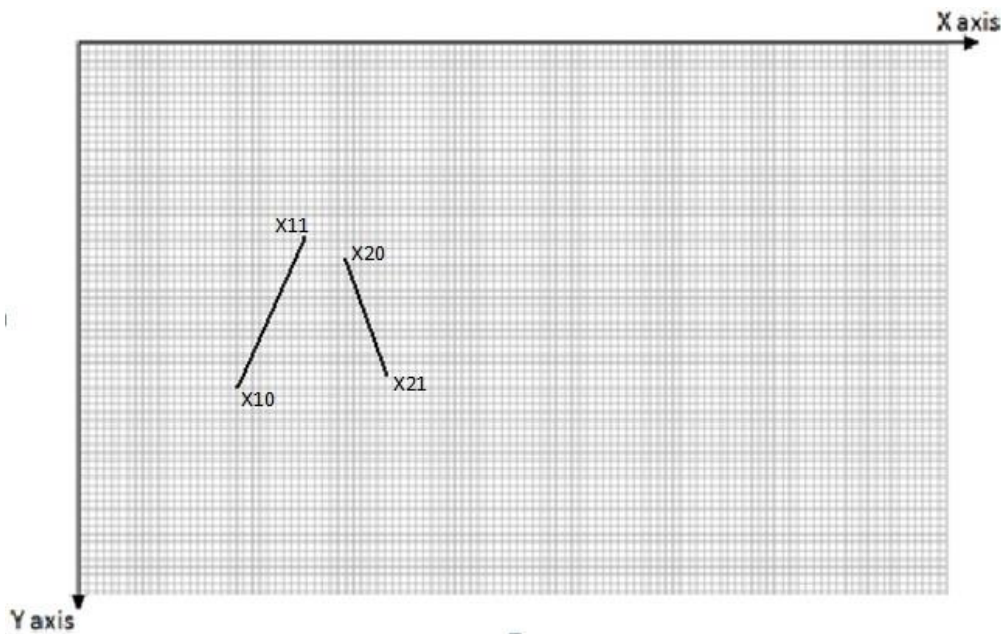


Figure 4-17: Sample thigh lines.

Flowchart of Filter D is shown in Figure 4-18.

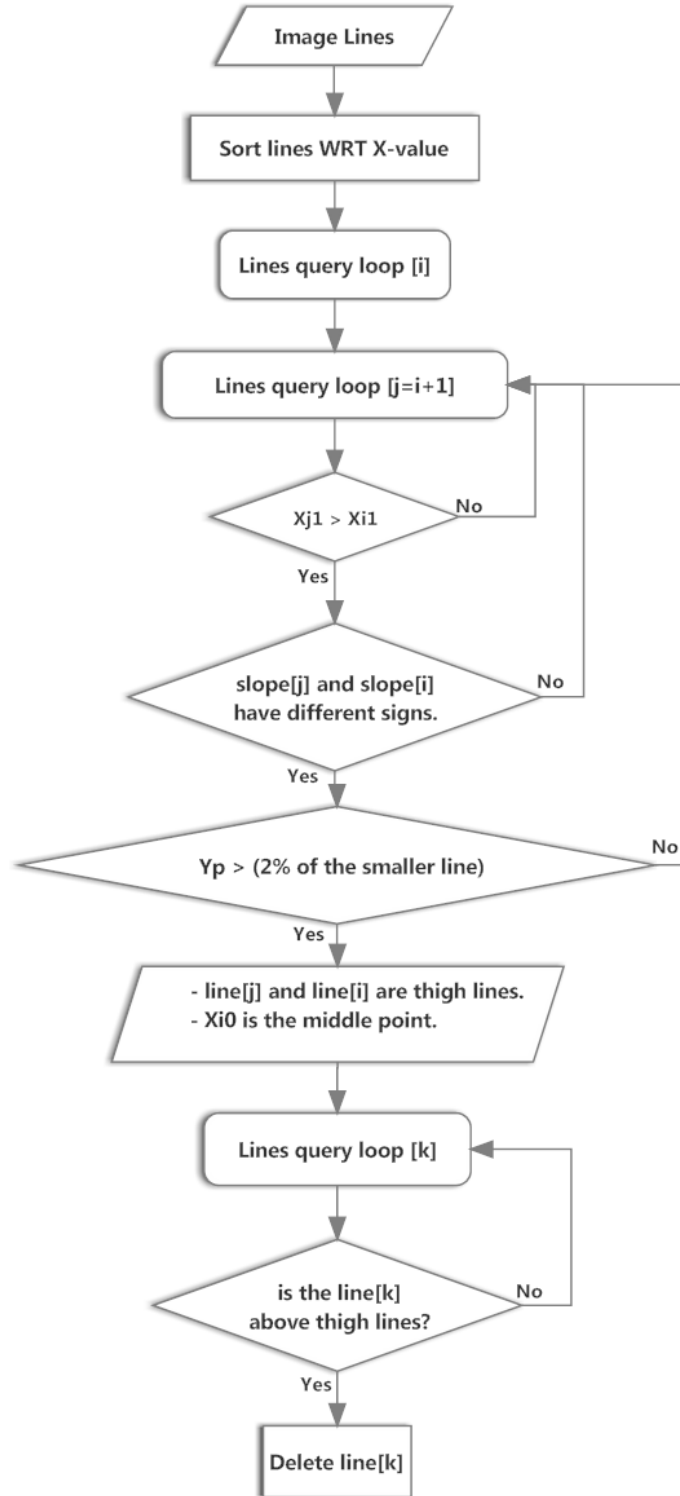


Figure 0-18: Illustration of Filter D.

Filter E is used to filter out lines of feet leaving the image with lines that represent thigh and leg. In Filter D, we determined the middle point which divides the lines to front and rear sides as it shown in Figure 4-19. In each side the first line which has the lower y-value represents the thigh line whereas the line below it represents the leg line and whatever lines under these two lines will be deleted.

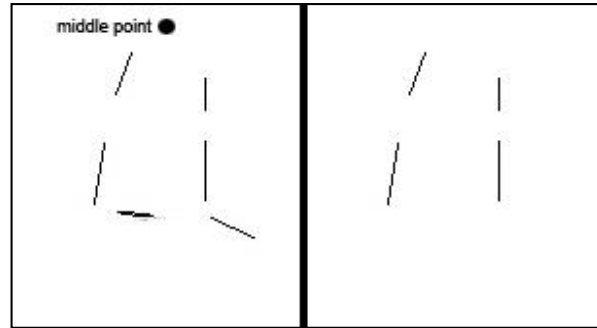


Figure 0-19: Illustration of Filter E.

Feature Extraction

At this point, all the undesired lines are expected to be filtered out leaving only the lines of thigh and leg. In order to extract gain signature, we assume movement of the right extremity and the left extremity are similar. This implies that there is no consideration which part is left and which one is right. This implies that we can process one extremity through a whole gait cycle or we can process the two extremities through one half of the gait cycle. The following variables are defined.

Max: maximum width;

Min: minimum width;

F: front extremity;

R: rear extremity;

As Figure 4-20 shows, gait cycle is assumed to start at maximum width [2] and end at maximum width [4]. There are two ways for which values to select. The first way includes selecting longer period extends from max[2] to max[4] by processing one extremity. This means that from max[2] to min[2], we take the front extremity (F1), from min[2] to min[3] we take the rear extremity (R1), and from min[3] to max[4] we take the front extremity (F2).

The second way includes shorter period that extends from max[2] to max[3], but in this way we process the two extremities. This means that from max[2] to min[2], we take the front and the rear extremities (F1 & R2) and from min[2] to max[3] we take the front and the rear extremities (R1 & F3).

Referring to Figure 4-20, the previously mentioned two ways are processed in a similar fashion as shown below. In this thesis, the second way is applied since it is expected to produce more accurate results.

First way: $F1 \rightarrow R1 \rightarrow F2$.

Second way: $F1 \rightarrow R1 \rightarrow R2 \rightarrow F3$.

After choosing the inclination values measured for both of thigh and leg in one gait cycle, the selected values are converted by Discrete Fourier Transform (DFT) into frequency domain.

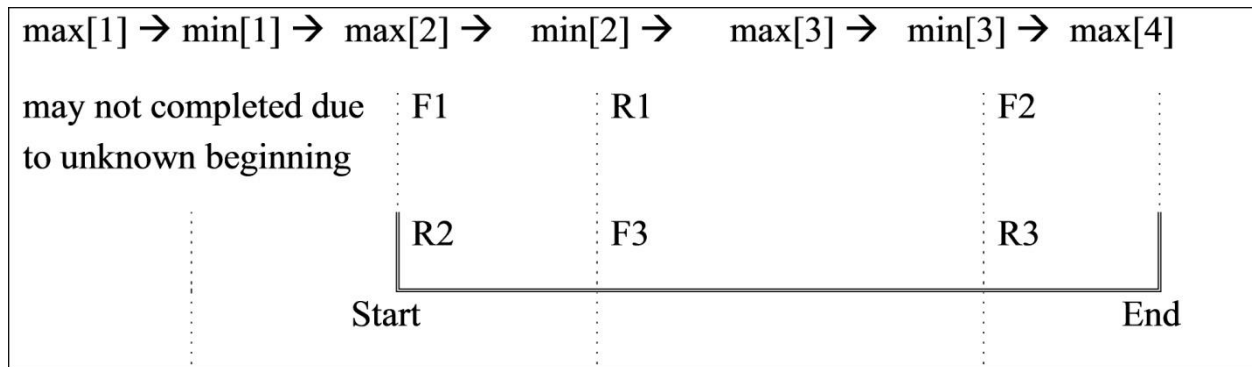


Figure 0-20: Feature Selection for One Gait Cycle.

The result obtained from DFT will be the Fourier transform of the selected gait features. In the training phase, all sequences are processed and gait features are extracted for each sequence. Then, selected features are converted by DFT. Finally, new features are stored in a text file as a gait signature database.

In the testing phase, a new sequence is extracted from the recorded video frame of a walking person. The sequence is processed and features of one gait cycle are extracted and converted into Fourier spectrum using DFT. The K-Nearest

Neighbor classifier is used to match the selected features from the sequence of the walking person with one set of features from the training gait signature database. If a match is found, the person is approved. Otherwise, the person is unauthorized.

CHAPTER FIVE

Experimental Results

Training Phase

Data are collected in an indoor/outdoor environment. Thirty two different subjects (persons) asked to walk in a path perpendicular to a 5MB stationary digital camera with their normal walking speed as shown in Figure 5-1.

Four samples (sequences) are collected per person resulting in 128 collected video frames. Each sequence has duration of about 2 to 3 seconds. The used video format is avi. Sixty four samples are used to train the developed gait recognition framework as shown in Table 5-1. For each sample (walking person), gait is captured (lower part of the body that contains thigh and leg). Then, features are extracted from the captured biometric gait. In other words, gait signature is extracted from inclination changes of both thigh and leg within one gait cycle. This indicates two features are extracted per person; thigh inclination and leg inclination. The extracted features of sixty four gaits are stored in a database file.



Figure 0-21: Illustration of Data Acquisition Process.

Table 5-1: Collected Samples for the Training Phase.

Subject Number	Sample Number	(Indoor/Outdoor)	Frame Rate
1	1	I	23
	2	I	23
2	1	I	23
	2	I	23
3	1	I	23
	2	I	23
4	1	I	23
	2	I	23
5	1	I	23
	2	I	23
6	1	I	23
	2	I	23
7	1	I	23
	2	I	23
8	1	I	23
	2	I	23
9	1	I	30
	2	I	30
10	1	I	30
	2	I	30
11	1	I	30
	2	I	30
12	1	I	30
	2	I	30
13	1	I	30
	2	I	30
14	1	I	30
	2	I	30
15	1	I	30
	2	I	30
16	1	I	30
	2	I	30
17	1	O	23
	2	O	23
18	1	O	23
	2	O	23
19	1	O	23
	2	O	23
20	1	O	23
	2	O	23
21	1	O	23
	2	O	23
22	1	O	23
	2	O	23

23	1	O	23
	2	O	23
24	1	O	23
	2	O	23
25	1	O	30
	2	O	30
26	1	O	30
	2	O	30
27	1	O	30
	2	O	30
28	1	O	30
	2	O	30
29	1	O	30
	2	O	30
30	1	O	30
	2	O	30
31	1	O	30
	2	O	30
32	1	O	30
	2	O	30

Results of the Gait Recognition Algorithm

Figure 5-2 shows a graphical representation of the dynamic change of the inclination of a person thigh moving through a single gait cycle, from heel strike to heel strike for the same leg. The steep and sudden rise in the curve comes at the moment of self-occlusion, where the legs cross each other, herein the direction of inclination changes from positive value to negative value and vice versa. Figure 5-3 shows a graphical representation of the dynamic change of the inclination of a person leg moving through a single gait cycle.

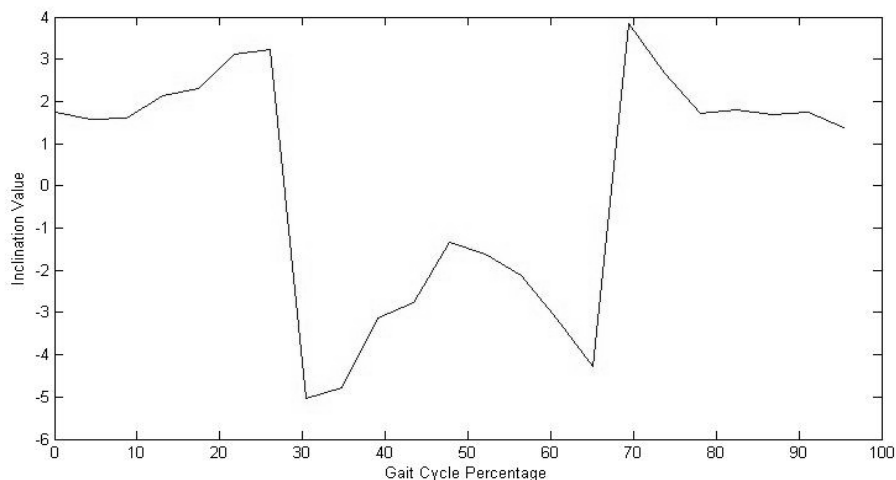


Figure 0-22: Dynamic Change of Inclination of a Person Thigh.

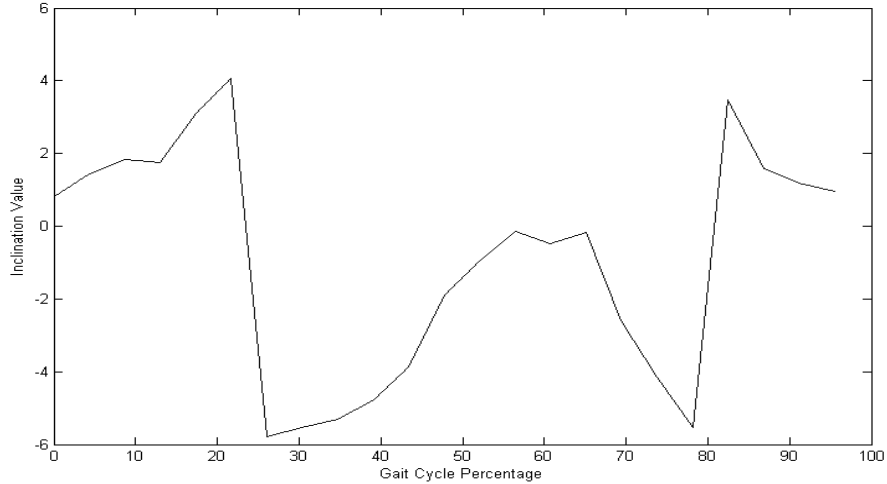


Figure 0-23: Dynamic Change of Inclination of a Person Leg.

To smooth noise and provide a better representation of data for better distance measurement-based classification, curve fitting is applied. Curve fitting is used to improve the appearance of graphed data through smoothing the data points. The Cubic Spline method is used for the curve fitting which is constructed from a series of cubic polynomial connected together because the inclination graph cannot be represented by single equation. The curve fitted plot of Figure 5-2 is shown in Figure 5-4 while the curve fitted plot of Figure 5-3 is shown in Figure 5-5.

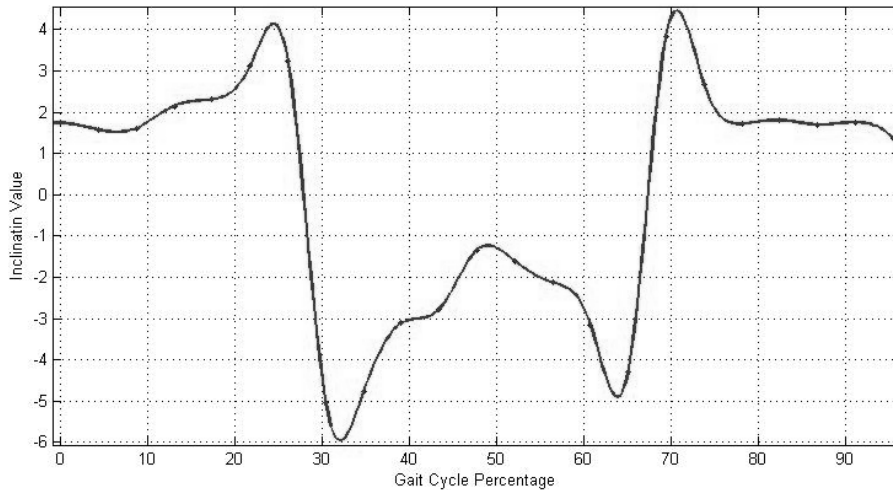


Figure 0-24: Result of Applying Curve Fitting to Figure 5-2.

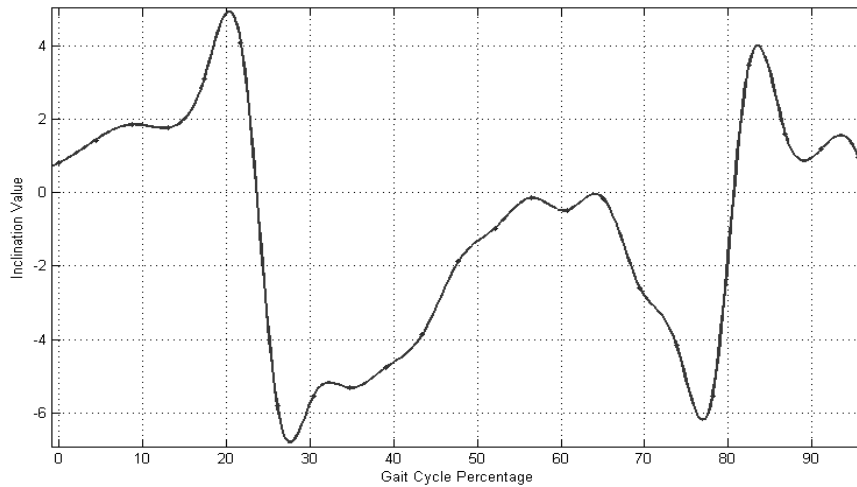


Figure 0-25: Result of applying curve fitting to Figure 5-3.

The obtained inclinations of Figures 5-2 and 5-3 are represented in time domain making them inadequate for achieving high recognition rates. Therefore, Fourier Transform is used to decompose the plotted signal into sinusoidal components better describe behavior of the walking person. Figure 5-6 and Figure 5-7 show the Fourier Transform applied to four gaits extracted from the same person for thigh inclination and leg inclination respectively.

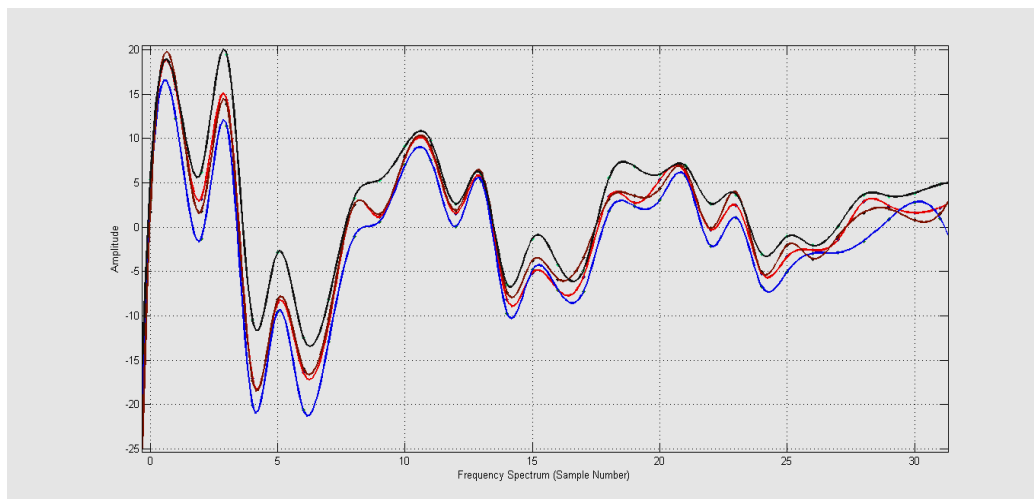


Figure 0-26: Fourier Spectrum for Thigh Inclination of Four Gaits of Same Person.

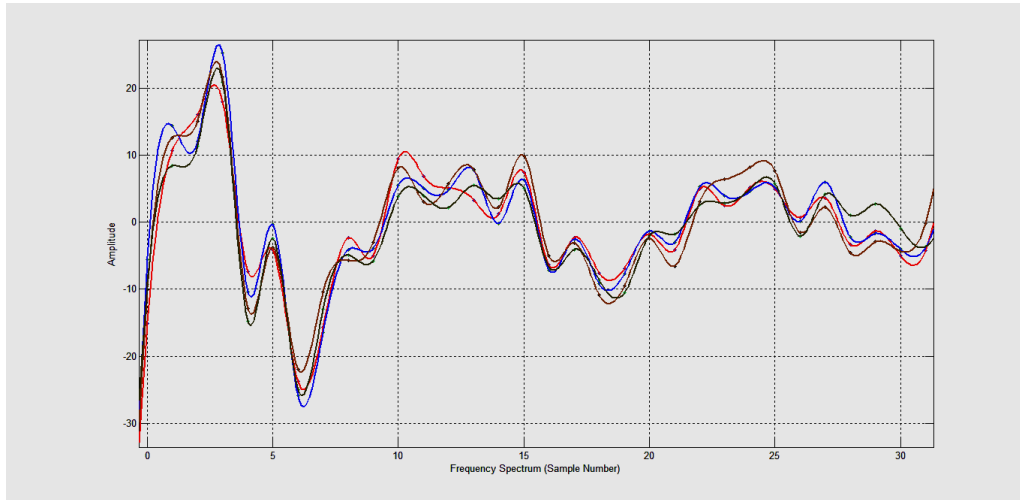


Figure 0-27: Fourier Spectrum for Leg Inclination of Four Gaits of Same Person.

For the background subtraction stage, K is set to 3 which represent the number of mixture components, the window size is set to 200 pixels, the number of Gaussians to model each pixel equals to three, and the standard threshold equal to 2.5. Figure 5-8 show the image sequence of the walking subject, and Figure 5-9 shows the output obtained from the background subtraction step.

Figure 5-10 shows the resultant image after applying the Silhouette extraction step. Next, the gait cycle is detected as illustrated by Figure 5-11. Then, the extracted silhouette contour is converted into skeleton image as shown in Figure 5-12. Next, Hough Transform is applied to the skeleton image to obtain an image with lines that represent body parts as shown in Figure 5-13.



Figure 0-28: Image of Gait Sequence.

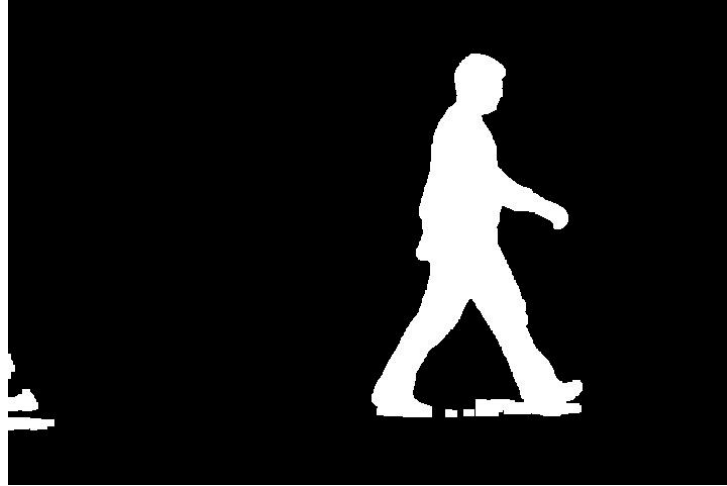


Figure 0-29: Extracted Foreground Subject after the Background Subtraction.



Figure 0-30: Extracted Silhouette after the Silhouette Extraction Step.

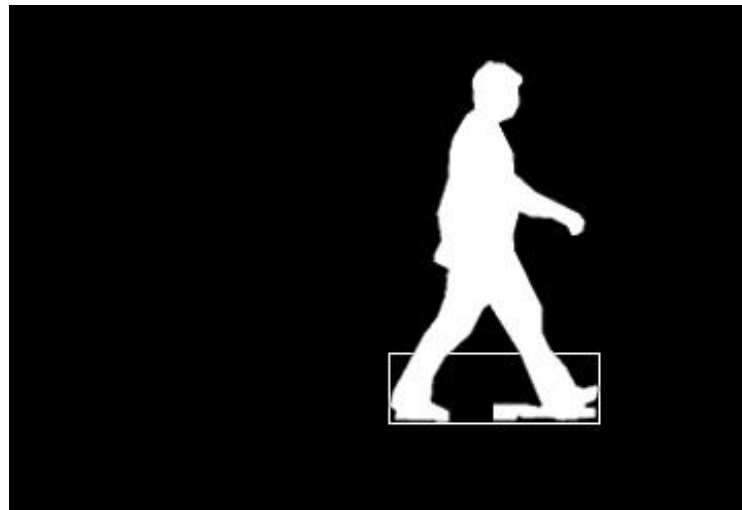


Figure 0-31: Gait Cycle Detection.

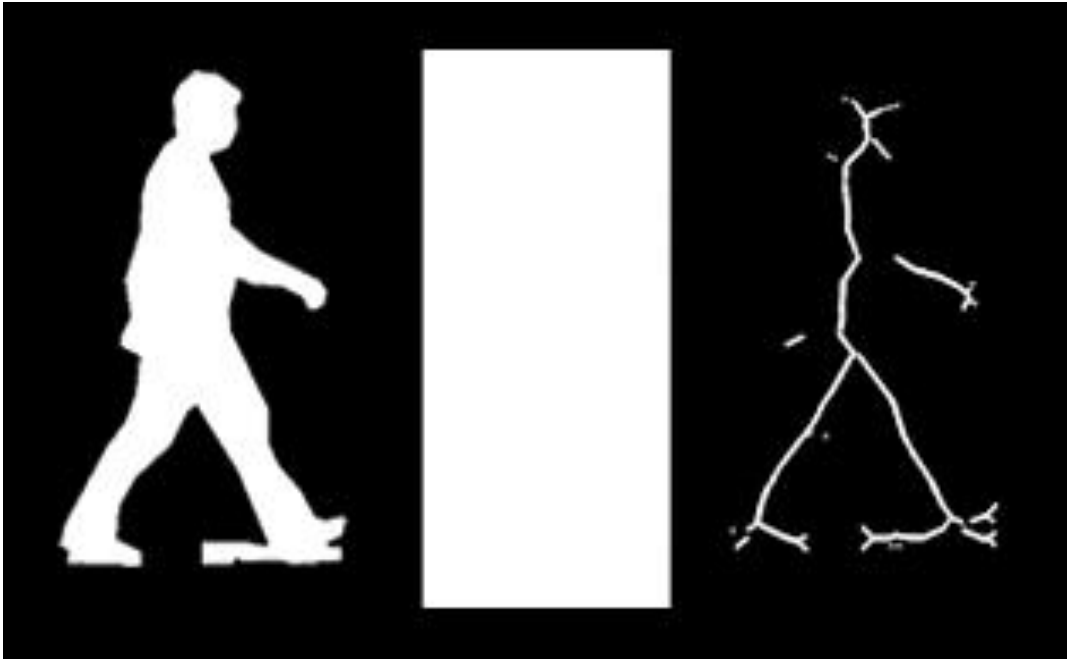


Figure 0-32: Extracted Skeleton.

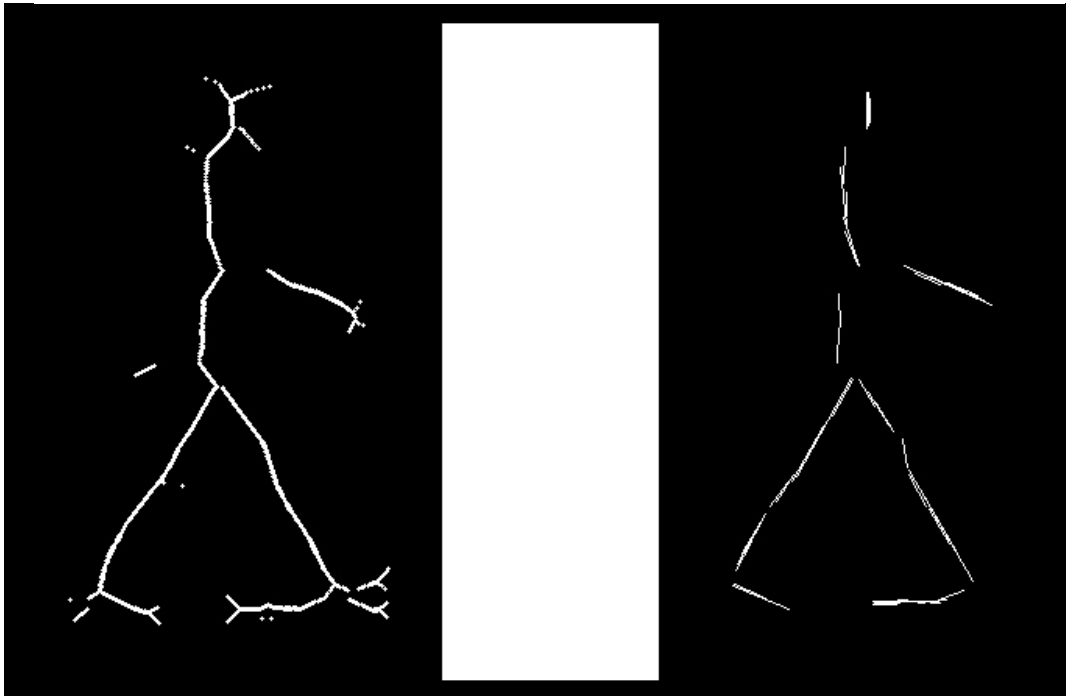


Figure 0-33: After Applying Hough Transform.

The developed Filters Line Algorithm first determines the upper and lower parts of the walking subject as show in Figure 5-14.

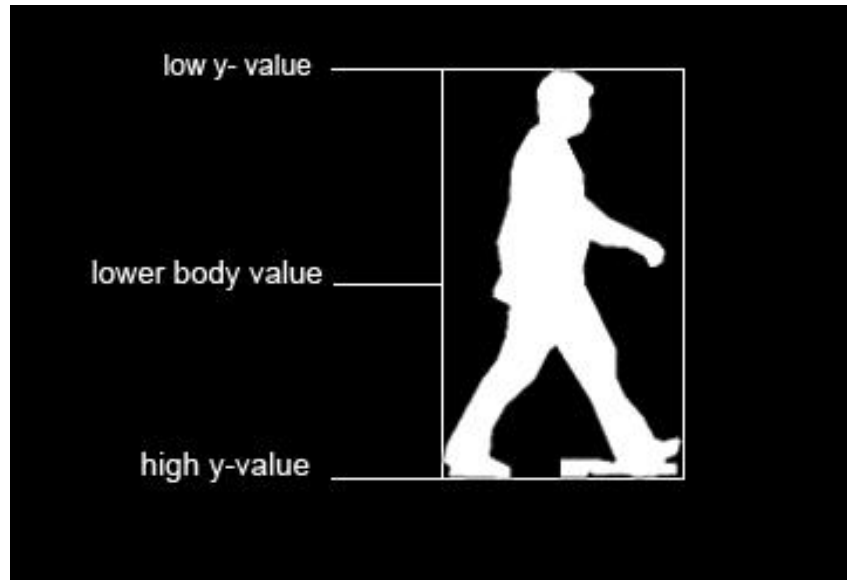


Figure 0-34: Dividing Walking Subject into Two Parts.

Figure 5-15 shows the truncated lower half of the walking subject.



Figure 0-35: Extracted Lower Half of Body.

Testing Phase

Sixty four samples are used to test performance of the developed gait recognition framework. Classification results are summarized in Table 5-2. A number of evaluation measures are used to assess the classification performance of the developed gait recognition framework. Accuracy is defined as number of correctly recognized persons over total number of persons used for the testing phase. We define false negative, FN, as the case of allowing unauthorized person to pass through the gate. False positive, FP, is defined as the case of preventing an authorized person from passing through the gate. Precision and recall are defined as follows:

$$Pc = \frac{TP}{TP + FP} \quad (1)$$

$$Rc = \frac{TP}{TP + FN} \quad (2)$$

where TP represents number of correctly recognized persons. The statistical analysis results of the developed gait recognition algorithm are summarized in Table 5-3. As the table indicates, the developed algorithm has a recognition accuracy of 90.63%. It only failed to detect one unauthorized person out of sixty four persons. It failed to recognize six authorized persons. Therefore, the developed framework has a high recall of 98.31% and precision of 90.63%. These results indicate the successful application of gait biometric in recognition applications.

Table 5-2: Testing Phase Results.

Subject number	Sample number	(Indoor/Outdoor)	Frame rate	FP	FN	Recognition (Yes/No)
1	1	I	23			Yes
	2	I	23			Yes
2	1	I	23			Yes
	2	I	23			Yes
3	1	I	23			Yes
	2	I	23		Yes	Yes
4	1	I	23	Yes		No
	2	I	23			Yes
5	1	I	23			Yes
	2	I	23			Yes
6	1	I	23			yes
	2	I	23			Yes
7	1	I	23			Yes
	2	I	23			Yes
8	1	I	23			Yes
	2	I	23			Yes
9	1	I	30			Yes
	2	I	30			Yes
10	1	I	30			Yes
	2	I	30			Yes
11	1	I	30	Yes		No
	2	I	30			Yes
12	1	I	30			Yes
	2	I	30			Yes
13	1	I	30			Yes
	2	I	30			Yes
14	1	I	30			yes
	2	I	30			Yes
15	1	I	30			Yes
	2	I	30			yes
16	1	I	30			Yes
	2	I	30			Yes
17	1	O	23			Yes
	2	O	23			Yes
18	1	O	23	yes		No
	2	O	23			Yes
19	1	O	23			Yes
	2	O	23			yes
20	1	O	23			Yes
	2	O	23	yes		No

21	1	O	23	yes		No
	2	O	23			Yes
22	1	O	23			Yes
	2	O	23			Yes
23	1	O	23			Yes
	2	O	23			Yes
24	1	O	23			Yes
	2	O	23			Yes
25	1	O	30			Yes
	2	O	30			Yes
26	1	O	30			Yes
	2	O	30			Yes
27	1	O	30			Yes
	2	O	30	yes		No
28	1	O	30			Yes
	2	O	30			Yes
29	1	O	30			Yes
	2	O	30			Yes
30	1	O	30			Yes
	2	O	30			Yes
31	1	O	30			Yes
	2	O	30			Yes
32	1	O	30			Yes
	2	O	30			Yes

Table 5-3: Statistical Analysis of the Developed Gait Recognition Framework.

FN Rate	FP Rate	Accuracy	Recall	Precision
1.56%	9.38%	90.63%	98.31%	90.63%

As classification is done via k-nearest neighbor, Table 5-4 shows the effect of number of neighbors, where k=1, 3, and 5.

Table 5-4: Effect of Number of Neighbors on Developed Framework Performance.

K	1	3	5
Recognition Rate	82.81%	90.63%	87.5%

Figure 5-16 shows the discriminatory capability of thigh and leg, which gives an indication to the importance of the features in recognition rate.

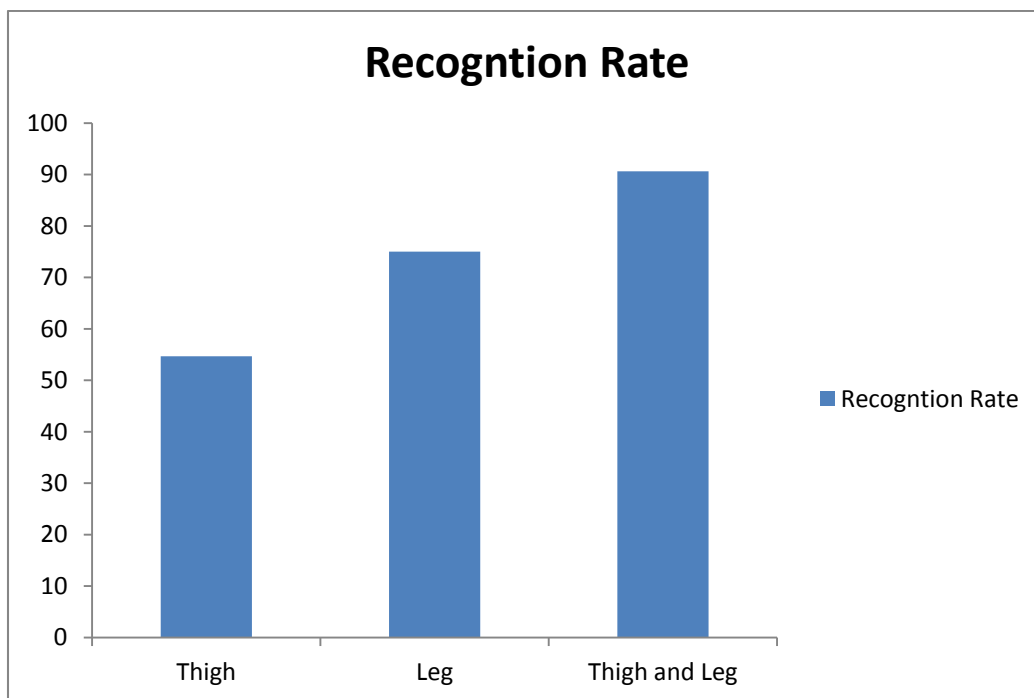


Figure 0-36: Overall Recognition Rate.

CHAPTER SIX

conclusion and future work

Conclusion

In this paper, a gait recognition framework is developed that offer easy video capturing, require low-cost tools, requires no contact with humans, and does not require a stripe to be painted on the person cloths.

The developed gait recognition framework consists of training phase and testing phase. Training phase is used to train the developed framework to be able to recognize authorized persons and prevents unauthorized persons from passing.

On the other hand, the developed framework consists of three stages. The first stage is intended to extract signature from the dynamic change of inclination of the person's thigh and leg. In the second stage, Filter Lines Algorithm is developed and used along with other methods to extract lines that represent thigh and leg and remove extra lines. In the third stage, K-Nearest Neighbor is used as a classifier.

Experimental results on sixty four samples indicate an accuracy, recall, and precision of 90.63%, 98.31%, and 90.63%, respectively. Thus the developed framework has a high recognition rate.

Future Work

The developed framework depends on human shape assuming the thigh and leg are within the lower half of human body. It also assumes that the person walking on a horizontally and smooth surface meaning that both thighs and legs have the same vertical line. Future work should focus on improving the framework to detect persons walking on uneven and non-smooth surfaces.

The developed framework provides a new way for gait recognition enabling researchers to implement this system on larger database with more challenges. The challenges are the variation states of the walking person, which may include the clothes, the surface, the carrying object, and the environment surrounded.

The dynamic features extracted in this work could be fused with static feature to complement each other, which in turn enhance the reliability of the gait recognition system. Finally, it can be linked with a system of surveillance cameras in security systems to be an effective real time identification system.

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