JULY 2016 M.Sc. in Electronics and Computer Engineering ZHYAR QAHAR

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GAIT-BASED GENDER CLASSIFICATION USING NEUTRAL AND NON-NEUTRAL GAIT SEQUENCES

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IN

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BY

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Supervisor(s)

Prof.Dr.Celal KORAŞLI

by

Zhyar Qahar MAWLOOD

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Zhyar Qahar MAWLOOD

Signature

ABSTRACT

A biometric system provides automatic identification of an individual based on his/ her unique feature or characteristic. Biometric identifiers are often categorized as physiological versus behavioural characteristics. Physiological characteristics are related to the shape of the body, like fingerprint, palm veins, face shape, while behavioural characteristics are related to the pattern of an individual’s behaviour, including gait, handwritten signature and voice. Gait as a means of biometric recognition aims to recognize a person by he/she walks. Human gait feature could be used in different applications such as identifying unauthorized persons, identifying their gender, and determining walking-related abnormalities by analysing the way they walk or move.

In this thesis we aim to propose gender classification based on human gait features to investigate the problem of non-neutral gait sequences: coat wearing and carrying bag conditions in addition to the neutral gait sequences. Our objectives will focus on investigating and testing the performance of gait sequence features for the purpose of gender classification. Our tests are based on large number of experiments using CASIA B gait database, includes 124 subjects (31 women and 93 men), recorded from 11 different view angles. For each subject, there are 10 walking sequences, consisting of 6 Neutral sequences (Nu), 2 Bag-Carrying sequences (CB) and 2 Coat-Wearing sequences (CW).

The proposed method mainly classified into three parts; the first part is focused on investigation of isolating conductive frames from their backgrounds using the frame differencing method.

The second part is related to feature extraction, for which we propose a new set of features which are constructed as based on the Gait Energy Image and Gait Entropy Image, called Gait Entropy Energy Image (GEnEI). Three different feature sets are structured from GEnEI based Wavelet Transform, called Approximation coefficient Gait Entropy Energy Image (AGEnEI), Vertical coefficient Gait Entropy Energy Image (VGEnEI), and Approximation and Vertical coefficients Gait Entropy Energy Image

(AVGEnEI). Finally two different classification methods are applied to test the performance of the proposed methods separately, called k-Nearest-Neighbour (k-NN) and Support Vector Machine (SVM). Further, these three sets of features are tested separately using the fused-based decision level fusion method.

We demonstrate that when k-NN is used as a classification method, AGEnEI results in 97% fusion level for Nu gait sequence, VGEnEI results in 91.4% fusion level for CB sequence and for CW sequence AGEnEI produces 83.6% fusion level. Among three sets of features, k=1 notably produces better average fusion level compared to the other two sets of features, i.e. k=3 and k=5.

When three sets of features (AGEnEI, VGEnEI , AVGEnEI) are fused using the decision level fusion method, we obtain accuracy of 99.8%, 92.2% and 86.3% for Nu, CB and CW respectively. These results outperform the results achieved when each of these sets of features are applied separately.

ÖZET

Nötr veya Nötr Olmayan Ardaşık Yürüyüş Tarzlarından Davranış-bağımlı Cinsiyet Klasifikasyonu

Biometrik sistem bireyle özleşik en çok göze çarpan bir özellik veya niteliğe dayalı bir vasıf kullanılarak bireyin tanımlanmasını sağlar. Biometric tanımlayıcılar genellikle davranışsal özelliklere karşı fizyolojik özellikler olarak kategorize edilir. Fizyolojik özellikler şahsın parmak izi, avuç içi damarlar, yüz tanıma gibi vücudun yapısal özellikleriyle ilgili olmasına karşın, şahsın davranışsal özellikleri yürüme tarzı, imzası ve sesiyle ilgili vasıflarıdır. Yürüyüş tarzı biometrik tanımlama yöntemi ile kişilerin erkek veya kadın olduğunun tanımlamasında kullanılacağı gibi kişilerin yürüyüş tarzları, yetkisiz kişilerin ve cinsiyetlerin belirlenmesi, ve yürüme veya yürümeye bağlı anormalliklerin tespiti gibi farklı uygulama alanlarında kullanılabilir.

Bu tezde, kişilerin yürüyüş özelliklerine göre cinsiyet sınıflandırması yapan bir yöntem önerilmiştir. Nötr yürüyüş dizilerinin yanı sıra palto/manto giyme (CW) ve çanta taşıma (CB) gibi nötr olmayan yürüyüş tarzlarından kaynaklanan tanımlama sorunları araştırılmıştır. Cinsiyet sınıflandırma amacıyla farklı yürüyüş tarzı dizinlerinin araştırılması ve denemelerinin yapılması üzerinde durulmuştur. Sayısal denemeler Casia B veritabanında mevcut değişik yürüyüş tarzları üzerinde çok sayıda denek üzerinde yapılmıştır. Bu veritabaında 11 farklı görünüm açılarından kaydedilen 124 kişi (31 kadın ve 93 erkek) bulunmaktadır. Her bir denek için, 6 nötr (Nu), 2 adet manto/palto giyme (CW) ve 2 adet çanta taşıma (CB) olmak üzere 10 yürüme dizini bulunmaktadır.

Önerilen yöntemin ilk bölümünde bir çerçeveli görüntüden arka planı çıkarma yöntemi kullanarak sırasal çerçeveli görüntüler ile arka planı arasındaki farkın hesaplaması üzerinde durulmuştur. İkinci bölümde Yürüyüş Enerjisi (Gait Energy) görüntü özelliklikleri yardımıyla sınıflandırma yöntemi incelenmiştir. Son olarak bu çalışmada bir sınıflandırma aracı olarak Yürüme Enerjisi Görüntü (Gait Energy Image) ve Rastgele Yürüme Enerji Görüntü (Gait Entropy Enerji Image, GEnEI) yöntemlri uygulanmıştır.

Wavelet Transformasyon tekniği ve GEnEI yöntemi kullanılarakveritabanından üç farklı yürüyüş tarzı özellikli görüntü grubu kurgulanmıştır. Bu yürüyüş tarzı özellikli görüntü grupları: (i) Yaklaşık Katsayı Rastgele Yürüme Enerji Görüntü (Approximate coefficient Energy Image, AGEnEI), (ii) Diksel Katsayı Rastgele Yürüme Enerji Görüntü (Vertical coefficient Energy Image, VGEnEI), ve (iii) her ikisinin birleşkesi olan Yaklaşık ve Diksel Katsayı Yürüme Enerji Görüntü (Approximate coefficient Energy Image and Vertical coefficient Energy Image, AVGEnEI).

Yukarıda belirtilen görüntüleme işlemlerinin işlevliliğinin denemesi için k-derece yakın komşu (k-Neraest Neighboor, k-NN) ve destek vector makinası (Support vector Machine, SVM) olarak bilinen yöntemler önerilmiştir. Ayrıca yukarıda belirtilen üç tür enerji görüntü yöntemi birleştirme tabanlı karar verme (fuse-based decirion level fusion) yöntemi kullanılarak da denenmiştir.

Sınıflandırmada k-NN yöntemi ile Nu gait dizinleri için AGEnEI % 97 lik ergitme seviyesini (fusion level), VGEnEI CB dizinleri için 91.4% lik ergitme seviyesini, ve AGEnEI CW dizinleri için %83.4 ergitme seviyesi sonuçları bulunmuştur. k=1, 3 ve 5 sayıları ile belirlenen üç ayrı özellik grubu arasında k=1 dikkate değer ergitme seviyesi sonuçları vermiştir.

Her üç enerji görüntüleme yöntemi (Energy Entropy Image) 'Decision-fusion' yöntemi ile birleştirildiğinde (fused) ergitme dereceleri Nu için %99.8, CB için %92.2 ve for CW için 86.3% dir. Bu sonuçlar her bir özelliğin ayrı ayrı ele alındığı durumunda elede edilen sonuçlardan daha iyi olduğu dikkate değerdir..

To my parents
My husband

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TABLE CONTENT

LIST OF FIGURE

LIST OF TABELES

pages

LIST OF ABBREVITION

A-USF: University of South Florida.

B- SOTON: Southampton University.

C- GEI: Gait Energy Image.

D- GEnI: Gait Entropy Image.

E- CASIA: Chines Academy Science.

F- DWT: Discrete Wavelet Transformation.

G- LL: Approximation.

H- HL: Horizontal.

K- LH: Vertical.

L- HH: Diagonal.

M- AGEnEI: Approximation Gait Entropy Energy Image.

N- VGEnEI: Vertical Gait Entropy Energy Image.

O- AVGEnEI: Approximation Vertical Gait Entropy Energy Image.

P- Nu: Natural gait sequences.

Q- CW: Coat Wearing.

R- CB: Carrying Bag.

S- FCV: Fold Cross Validation..

T- K-NN: K-Nearest Neighbor.

U- SVM: Support Vector Machine.

CHAPTER 1

INTRODUCTION

1.1 General Feature of Gait Recognition

Recognition of an individual is a necessary task to identify people. Biometric comes from the Greek words contain two words bios(life),and metric(measure).The meaning of biometric system in today’s world has been maintained by the large-scale identity management systems whose functionality relies on the accurate determination of an individual’s identity: ID cards, punch, a secret password, and PIN used for personal identification. A biometric system runs automatic identification of an individual, based on a unique feature or characteristic possessed by the individual. In the biometric system, there are basically two identifiers that biological system uses. These identifiers are classified as physiological and behavioural characteristics [1].

i. Physiological features are connected to the shape of the body, like fingerprint, palm veins, face recognition. A physiological biometric might distinguish by one's voice, DNA, hand print or behaviour.

ii. Behavioural features are connected to the pattern of behaviour of a person, including gait, handwritten signature, and voice. Behavioural features can be recognized by identification systems which are designed to determine identity based on gait features.

One of the main the parameter in behavioural characteristics of an individual which is the subject of the represent study is its walking behaviour known as gait identifier. To use walking gait as a biometric system is strongly motivated by the need for an automated recognition system for visual surveillance and monitoring applications.

Generally we can divide gait analysis into two parts: [2]

a. Gait recognition where identify subject’s ID in specific.

b. Gait classification which includes gender classification, action classification, and estimation of age.

There is a lot of research related to human gait recognition, but only a few recent works used gait for gender classification. Gender classification can applied in different applications e.g. smart surveillance systems that can assist in restricting area to one gender only, such as in banks, computer centres, private offices, airports etc.[2].

Among the forms of biometric identification techniques, gait biometric can be considered as the most beneficial form due to:

- Unobtrusive: The person walking gait can be gained while she/he is unaware of the process during the analysis. In other words, the process of collecting data does not involve user's cooperation unlike fingerprint or retina scans.
- Distance recognition: Different from fingerprint recognition in that individual gait can be obtained from distance.
- Detail reduction: Gait recognition needs simple images without demand for high quality images which can be affected easily such as in face recognition.

Unlike other biometric techniques such as face recognition in which the person's face can be adapted, in the gate technique disguising is very difficult and even if it is done, the individual will be suspicious

- Difficult to conceal – The gait of an individual is difficult to disguise, by trying to do so the individual will probably appear more suspicious. With other biometric techniques such as face recognition, the individuals face can easily be altered or hidden [3].

1.2 Characteristics of Biometric

Any human phsyological characteristics could be used as a biometrics characteristics as long as they satisfiy the following requirements:

i. Universality: each person should have the characteristics.
ii. Uniqueness: any two people should be sufficiency different in terms of the characteristics.
iii. Permanence: the characteristics should be sufficiency invariant over a period of time.
iv. Collectability: The biometric characteristic should be measurable with some practical sensing device.
v. Performance: which refers to achievable recognition accuracy and speed the resources required to achieve the desired recognition accuracy and speed ,as well as the operational and speed.
vi. Acceptability: The particular user population and the public in general should have no (strong) objections to the measuring/collection of the biometric characteristic.
vii. Resistance to Circumvention: Refers to the degree of difficulty required to defeat or bypass the system [4].

1.3 Popular Biometrics Traits

Based on different types of biometric modalities, two basic branches can be identified: physiological and behavioral . The followings are some popular biometric traits[1,2].

1.3.1 Finger Print Recognition: Fingerprint recognition is based on recognition of the fingerprints. The structure of a fingerprint's ridges and valleys are recorded as an image or digital template (a simplified data format) ,then the difference with other images or templates are used for authentication or verification [5].

1.3.2 Voice Recognition: Voice is a combination between physical and behavioral biometric character .The physical feature of an individual voice are based on shapes and the size of appendages e.g. (mouth and lips)that are used for synthesis of the sound [6].

1.3.3 Iris Recognition: Iris recognition is a specific kind of biometric system. The complex iris texture carries very particular information utilizes for personal recognition exactly and speedily. The iris based recognition system is promising and support the feasibility of large-scale identification system based on iris information [7].

1.3.4 Face Recognition: Face recognition is a form of a physiological biometric recognition system that is aiming to recognize the individual from a distance. The structure of the face is recorded as an image or digital template to be used for correlation [8].

1.3.5 Signature Recognition: Signature is a behavioral modality that uses for recognition. A signature must be handled as an image, and recently it can be recognized after storing and utilizing it as computer vision [9].

1.3.6 Hand Geometry: Biometric handwriting recognition is behavioral biometric system that converts characters and a writing sample into mathematical graphs. The graphs contain enough information to be extracted as features of handwriting that are unique to each individual. Handwriting identification is often used to supplement to the other biometric technologies [8].

1.3.7 Palm Print: The palm of the human hands consists of a pattern ridge and valleys much like the finger print. The area of the palm is much larger than the fingerprint, hence the result of palm print is expected to be even more distinctive than the finger print [10].

1.3.8 **Gait Recognition:** Gait recognition is a part of behavioral biometric . Gait as one of the biometric recognition aims to recognize a subject by the way they walk [2]. The goal of gait recognition is to recognize pedestrians regardless of interference from background and clothing This biometric trait is the subject of the resent work More details are provided in Chapter 3.

1.4 Gait Feature Challenge [3]

Conducting both biometric gait recognition approaches are beneficial .Since some factors may negatively and behavioral affect to these both approaches. Factors that affect biometric gait system can be classified into two groups (not necessarily disjoint): First factor is external, and this factor forces challenges toward recognition approach (or algorithm). For instance, viewing angles (e.g. frontal view, side-view), lighting conditions (e.g. day/night), outdoor/indoor environments (e.g. sunny, rainy days), clothes, walking surface conditions (e.g. hard/soft, dry/wet grass/concrete, level/stairs, etc.), shoe types (e.g. mountain boots, sandals), object carrying (e.g. backpack, briefcase) etc.

On the other hand, internal factor adapts the natural gait as a result of sickness (e.g., foot injury, lower limb disorder, Parkinson disease etc.) or other physiological changes in body because of aging, drunkenness, pregnancy, gaining or losing weight and so on.

1.4 Problem Description and Aim of the Present Work

Gender classification can be applied for different purposes, and it can be used as a first step in biometric recognition system for the purpose of efficiency and improving the accuracy. In most of the gait-based gender classification methods human gait features are extracted from neutral gait sequences. However, In a real life scenario this is unfortunately not the case; human walks under different covariate factors including footwear, clothing, walking speed, carry bags etc. These factors introduce some challenges when trying to classify human's gender by gaits.

With these challenges in mind in this thesis we aim to propose gender classification system based on human gait features. As mentioned before there are two main factors that affect gait feature; external and internal factors, in this thesis as addition to using Neutral gait sequences, we aim to investigate carrying bag and coat wearing gait sequences (are included of the external factor) to present more realistic scenario and highlight the effect of bags and coats on gait-based gender classification.

The remainder of this project is organized as follows, Chapter2 contains literature review and characteristics of dataset used in gender classification. Gait representation and feature extraction are described in Chapter3. Which includes the methods applied in the result and conclusion. provides classification and Experiments and results are presented in Chapter4 and Chapter5 presents conclusion and future work .

CHAPTER 2

LITERATURE REVIEW AND GAIT DATASET

2.1 Difficulties of Gender Classification

This study aims to investigate the classification of gender by gait recognition as a part of biometric system. Within gate recognition, walking gait analysis is considered as an essential issue due to its sensitivity to insufficient segmentation of the subject silhouette, variety in footwear and/or clothing, change in the pattern of the gait model resulted from carrying objects or modifying walking speed etc. As a result of these difficult issues, there is inadequacy in public databases regarding the variety between gait samples [1]. Also this shortage might be due to insufficient number of related researches.

2.2 Gait Features

Gait-based gender classification contains recognizing the gender based on humans walking, climbing, running and jogging etc.. Hu et al., [11] noticed that the classification accuracy rate decreases with extra objects helping to daily life and attached to body such as carry bag or wear overcoat. Gait-based gender classification techniques are divided into two categories: model-based and model-free.

(i) Model-based methods attempt to explicitly model the human body or motion by employing static and dynamic body parameters. Different approaches been make use of features like distances or angles between different human body parts, trajectories of joint angles, head or feet using 2D stick models, motion parameters using 3D temporal models, or a combination of kinematics and appearances of a gait [12].

(ii) Model-free approaches, on the other hand, usually utilize either shape of binary silhouettes or all motion of walking person’s body, indeed modeling covers the all human body or any part of it [13].

These approaches are insensitive to the quality of silhouettes and have the advantage of low computational costs. However, they are usually not powerful to problem assocated with changes and scaling Some examples of this category are template matching of silhouettes. In this project, we focused on gait gender classification using gait more importantly to different features like carrying bag and coat wearing.

2.3 Literature Review

The Gender classification approaches for human identification plays an important role in many applications especially in security systems.Shiqi Yu et al.[14] proposed gender based classifier for gait analysis. Human able to recognize people based on gait. They have used numerical analysis on human components and identified discriminative human components. They have done cross-race experiments to prove gait based classification of gender is achievable in controlled environments. They have used CASIA data set and they correlated their classification rate with other algorithms. They have noted that gait recognition suffers from many difficulties like view variation, clothing shoes change and carrying objects.

Barclay et al. [15] carried out more research on gender recognition. They investigated the affected of spatial and temporal factors for correcting classification rate. The result indicated that at least two gait cycles are necessary for successful gender recognition. The speed of walkers also have been shown important effect for on classification accuracy. In their experiments, the highest recognition accuracy is 68%. Most of the studies were based on the side-view presentation of walkers to observers. On the other hand, some experiments were tried to find the effect of view angle on gender recognition. It was found that the front-view presentation contains more information than side-view for gender recognition.

Troje [16] recently used linear pattern recognition technique to deal with the analysis of biological motion, and presented a two-stage PCA framework for recognizing gender. He reported 92.5% recognition rates.

Davis and Gao[17] used gait features for gender classification to displays in an automatic method. The method proposed uses an adaptive three-mode PCA to extract features from point-light displays. The most suitable and correct classification rate (CCR) in the 40 database subjects (20 females and 20 males) was found to by 95.5%. They also recruited 15 observers to recognize gender by watching moving point-light displays on a computer monitor. The CCR was found to be 69% which is within the acceptable range.

The most popular method to achieve gender recognition is based on biological motion point-light displays. Kozlowski and Cutting [18**]** were the first researchers who began to study on gender recognition from human walking manner. It has been demonstrated by them that the observers are capable to acknowledge the point-light walkers' gender.

Lee and Grimson [19] found static features that describe the silhouette appearance of a human walking for person identification and gender recognition. The process of a segmentation practiced to video frames so as to extract human silhouettes, which have been normalized regarding size and location. To represent appearance, the human silhouettes have been divided into seven regions that could be fitted with ellipses. To represent movement (changes in silhouette poses across the frames), some parameters of the ellipses model of the same region were performed across all the frames of the sequences, which result in a set of 57 attributes per sequence. The classification experiments on the MIT Gait Database (MIT,2001) lead to an accuracy close to 80%.

Liang Wang et al., [1] suggested spatial-temporal silhouette analysis. They have suggested for each sequence of the background image in subtraction procedure for segmentation, algorithm, Eigen space transformation based PCA is used to reduce dimensionality of the image sequence and supervised algorithm is used for classification of gait. They have also performed more work on gait with viewing angle, unconstrained environment, and clothing. Their future enhancement is to develop more sophisticated gait classifier.

Mather and Murdoch [20] have found that shoulder influence was a compelling prompt to gender orientation at the frontal perspective. Although the vast majority of the study were led utilizing a side-view presentation of the walkers to the perceivers, the impact of the perspective point on gender acknowledgment execution was analyzed. A significant part of the past studies has concentrated on the manual designation of key components that empower the perceptual order amongst female and male strolling styles. Highlights identified with rate, arm swing, shoulder–hip lengths, reversal, and body influence have been analyzed. In any case, to date, there is no decisive confirmation as to which highlights really drive the separation procedure.

Yu et al.[21] performed another research dealing with different appearance-based method for gait-based gender recognition that was tested on the CASIA gait database. Given a sequence of gait silhouettes, a Gait Energy Image (GEI) is created by combining them.The GEI is aparted into 5 body part, head/hairstyle, chest, back, waist/buttocks and legs, which are weighted as regards a previous psychological study. Experiments involved a single subset composed of 31 women and 31 randomly selected men that fed a Support Vector Machine with a linear kernel. The best classification result was an accuracy of 95.97%. Nevertheless, the use of only one subset raises doubts about the reliability of the result.

Sajid et al.,[22] stated that the practical applications of gender classification are suffering from the problems like high data dimensions and different facial variations. They discarded the background region and detect only the facial portion. The input image is converted into four new images namely LL, HH, HL and LH using 2-D Wavelet Transform (DWT). The new four images represent the details and approximate coefficients of the image respectively.Some of the irrelevant features are eliminated after applying Principle Component Analysis (PCA) . SUMS database is used for experiments and training to testing ratio of 50 to 60 is maintained. Proposed technique is found more accurate to recognize gender by utilizing less number of feature sets.

SitiZura A. et al [23] depicted examination of body utilizing human radiation recurrence gender order. The human radiation recurrence is tentatively studied from 33 solid humans. They utilized 17 males and 16 females, and KNN as a classifier is utilized for sex grouping. They initially investigated crude information set and post handling dataset and afterward they think about their order of the results. They obtained accuracy of 93.8%.

Michelle Karg et al.,[24] recognized gait at distance. They have addressed inter-individual and person dependent recognition. They have compared PCA, kernel PCA, linear discriminant analysis and general discriminant analysis to extract relevant features for classification and to reduce temporal information in gait. They attained 95% of accuracy in person-dependent recognition by observing the stride length.

2.4 Gait Datasets

Almost all gait researchers used the same gait dataset for their experiments due to its efficiency. Standard publically available gait datasets are needed to compare and evaluate the performance of gait recognition algorithms. Create own dataset will need more time because of some factors like a number of people for gait subjects. External factors also giving more effect like lighting and big space room for video shooting. Good hardware specification like installation of a video camera rather than one camera. There are basically three gait datasets:

1. USF gait datasets developed by University of South Florida ,USA.
2. SOTON gait dataset developed by University of Southampton, UK.
3. CASIA gait dataset which is the famous among the others developed by Chinese Academy of Sciences.

1. **USF Database:** The database USF make up of 33 ordinary subjects. This data set makes up of walking person in the elliptical paths in front of the camera(s). Each person have been walked repeatedly or it can said multiple (>= 5) circuits around an ellipse. The following circumstances are included in this dataset.
    - different shoe types (A, and B),
    - different carrying conditions (with or without a briefcase),
    - on 2 different shapes type (grass and concrete),
    - from 2 different viewpoints (Left or Right) and
    - some at 2 different time instants

Moreover, there are 32 possible circumstances which are under the persons gait which is under control or it could be said imagined. However, not all the subjects were imaged in all the circumstances. The full data set are partitioned as depicted in the following grid shown Figure 2.1 [25].

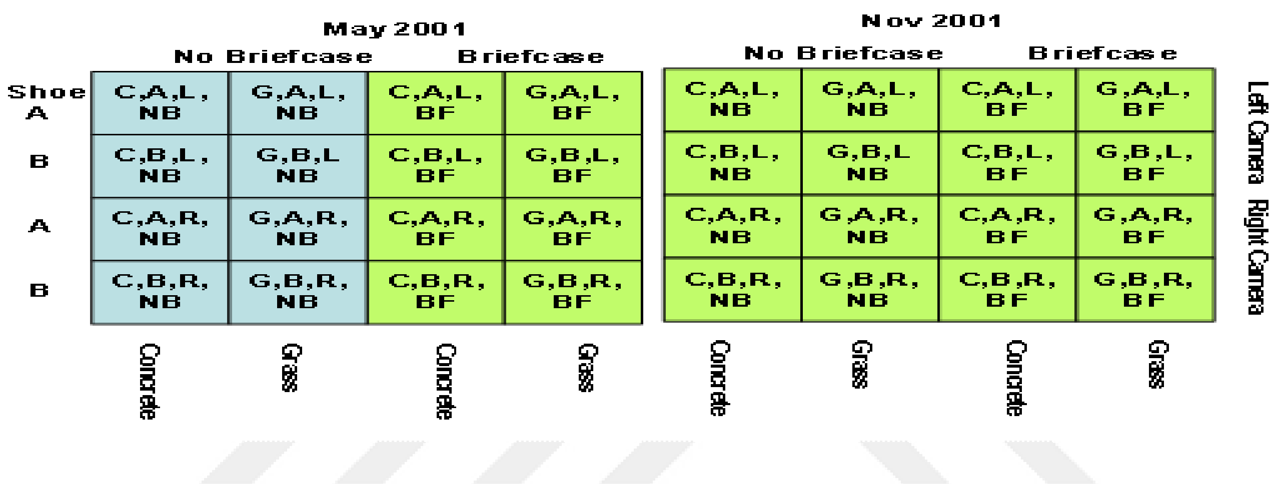


Figure 2.1 USF Data base [25]

(C- Concrete , G-Grass ,A-Shoe type A, B-Shoe type B, L-Left camera, R-Right camera, BF-Briefcase, NB- No Briefcase)

2. **SOTON database:** Gait Dataset is a Human ID gait database at a distance consists of two major segments:
   - a large population (~100), but basic database.
   - a small population, but more detailed, database.

The large database is represented with two questions, the first one is about the analysis of individual gaits through significant number of human under normal circumstance, and the second one is the limitations toward the biometric algorithms or towards the computer sight algorithms for accurate extraction of subjects. Hence the small database is contracted to investigate the robustness of the biometric techniques to the imagery of the same subject in the different common circumstance such as (carrying items, wearing different clothing or footwear) [26].

3. **CASIA database** [27]**:** This a gait data base which has been widely used by the researchers at the present time. In this study, we used CASIA dataset as a resource for gait-based gender classification dataset resource.

   Dataset made up of four subjects:

   (i) **Dataset A** (standard dataset).
   (ii) **Dataset B** (multi-view gait dataset).
   (iii) **Dataset C** (infrared gait dataset).
   (iv) **Dataset D** (gait and its corresponding foot print database).

(i) **Dataset A**: This dataset includes 20 persons. Each person has 12 image sequences, 4 sequences for each of the three directions, i.e. parallel, 45 degrees and 90 degrees to the image plane. The length of each sequence is not identical for the variation of the walker's speed, but it must ranges from 37 to 127. The size of Dataset A is about 2.2GB and the database includes (19139) images (Figure2.2).

Figure 2.2 Dataset A of CASIA Database [27].

(i) Dataset B: It is a large multi view gait database. There are 124 subjects, and the gait data was captured from 11 views (Figure 2.3). Three variations, namely view angle, clothing and carrying condition changes, are separately considered. Besides the video files, it also provides human silhouettes extracted from video files. The format of the video filename in Dataset B is ‘xxx-mm-nn-ttt.avi’, where

- xxx: subject id, from 001 to 124.
- mm: walking status, can be ‘nm’ (normal), ‘cl’ (in a coat) or ‘bg’ (with a bag).
- nn: sequence number.
- ttt: view angle, can be ‘000’, ‘018’, …, ‘180’.

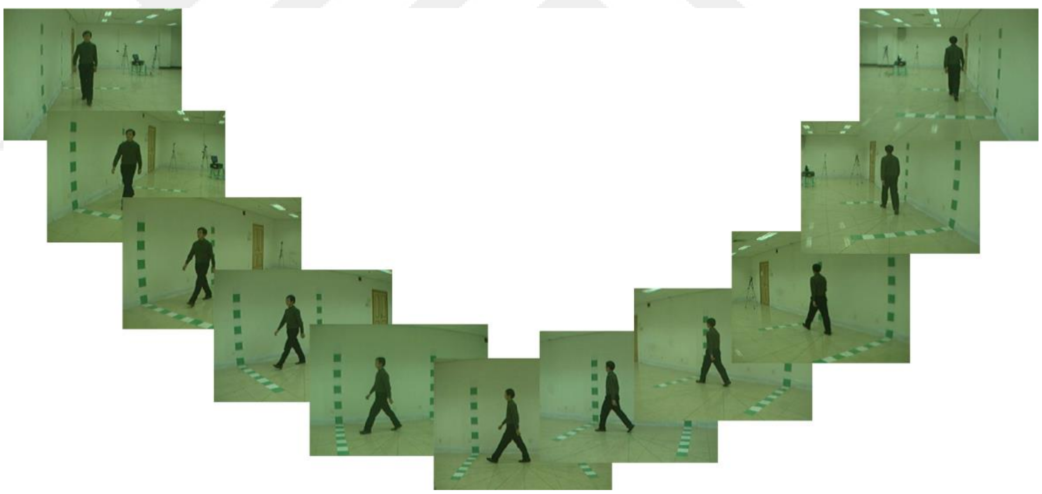


Figure 2.3 CASIA database dataset B [27].

We used Class B CASIA Dataset [27]. CASIA Class B is a large multi-view gait database under imbalanced conditions. There are walking subject 124 clear subjects, 93 Male and 31 Female and the gait is taken from 11 different view Angeles. For each subject there are 10 walking sequences consisting of 6 Neutral (Nu), 2 Carrying Bag(CB) and 2 Coat Wearing (CW). In the present research work we make use of Class B of CASIA database for gender classification.

(ii) Dataset C: Is a dataset of 153 subjects and. It takes into account four walking conditions; normal walking, slow walking, fast walking, and normal walking with a bag. The videos were all captured at night (Figure 2.4)

The format of the video filename in Dataset C is ‘01xxxmmnn.avi’, where

- xxx: subject id, from 001 to 153.
- mm: walking status, can be ‘fn’ (normal), ‘fq’ (fast walk), ‘fs’ (slow walk) or ‘fb’ (with a bag).
- nn: sequence number.

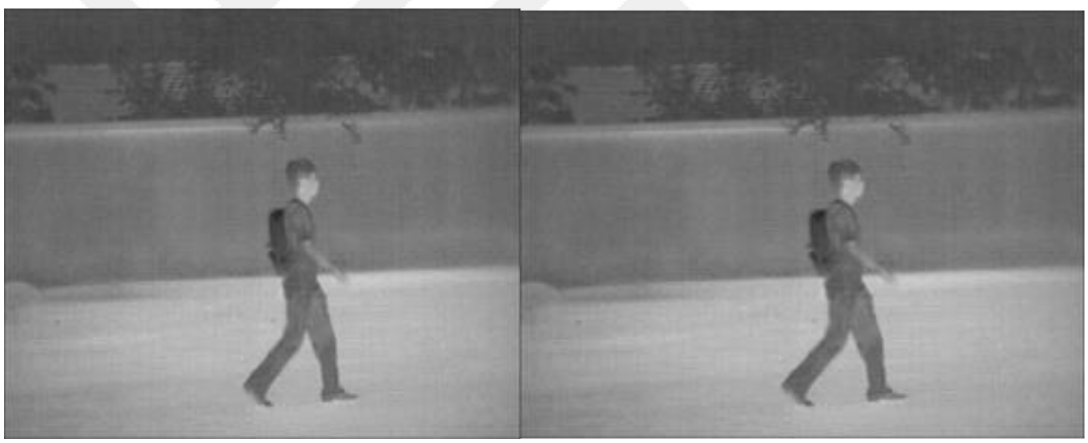


Figure 2.4 Dataset C of CASIA Database [27].

(iv) Dataset D: Is also a synchronously collected database. It contains 88 subjects and takes into account real surveillance scenes and wide age distribution. This dataset can be considered as the attempts in exploiting the relations between behavior biometrics and its corresponding prints.The videos and images are collected indoor, while all the subjects are Chines. (Figure 2.5)

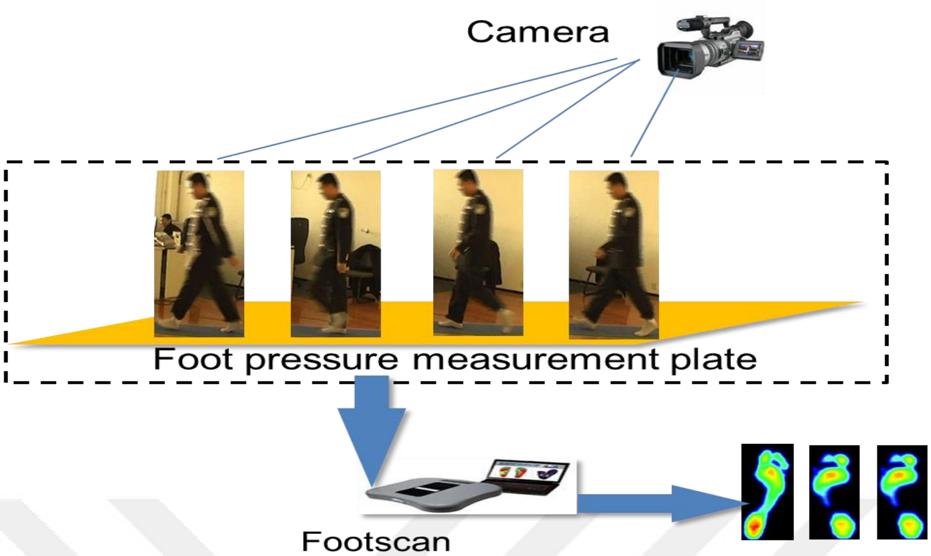


Figure 2.5 Dataset D of CASIA Database [27].

CHAPTER 3

METHODOLOGY

In this chapter the basic steps to be followed in gender classification will be explained. There are several steps to solve any type of classification problem; the method of gender preprocessing, subtracting background, creating box boundary around silhouette image, normalizing gait cycle estimation, feature extraction, reduction of dimensions, and finally classification recognition.

3.1 Preprocessing

Pre-processing is an important step during gait recognition process. The aim of pre-processing is to improve the image (frame) data which overwhelms undesired distortion or enhances some image features related to further processing and analysis task. In the research of gender classification method the pre-processing is used to perform background subtraction , normalization and gait cycle estimation as explained in the following sections[28].

3.1.1 Background Subtraction

This is a technique applied in the fields of image processing and computer vision. The background subtraction is used to extracted foreground image from the background image for further processing (human body recognition etc.). Background subtraction technique is a widely utilized approach for detecting moving objects in videos from static cameras. Generally, the regions of interest of an image are the objects (humans, cars, text etc.) in its foreground. After the phase of image preprocessing (which may include image missing, post processing like morphology etc.) object localization is required to which background subtraction algorithm is applied. With this technique we can   handle lighting changes, repetitive motions from clutter and long approach scene [28].

The following analyses make use of the function of V(x,y,t) as a video sequence where t is the time dimension, x and y are pixel area variables. e.g. V(1,2,3) will be those pixel intensities at (1,2) pixel area of the picture during t = 3 in the video sequence. Frame reference (absolute) at time t + 1 is expressed as.

$$D(t+1) = |V(x,y,t+1) - V(x,y,t)| \tag{3.1.1}$$

The background is assumed to be the frame at time t. This difference between images could only show some intensity for the pixel locations which have changed in two frames, seemingly removing the back ground image. This method will only work for the cases where all foreground pixels are moving and all background pixels are static. A threshold "th" is inserted on this difference as a constraint to improve the subtraction process.

$$|V(x,y,t) - V(x,y,t+1)| > th \tag{3.1.1.2}$$

The exactness of this approach is dependent on speed of movement in the scene. Faster movements may require higher thresholds [28]. Figure 3.1 shows two steps before and after the background subtraction.

(a) **(b)**

Figure 3.1 Process of background subtraction (a) Clustered image (b) Image after background subtraction.

3.1.2 Gait cycle estimation

The gait cycle is described as the motion of the human image frame from its initial placement at one of the heels supporting heels at a point on a ground when the same heel contacts the ground for the second time. A gait cycle is composed of one right leg step and one left leg step. As shown in Figure 3.2 the gait cycle is divided into two phases; stance, and swing.

(i) Stance is included in the interval in which the foot is on the ground (about 60% of the gait cycle).

(ii) Swing, on the other hand, is included in the interval in which the foot is not in contact with the ground (about 40% of the gait cycle).

The gait cycle of the motion is started when the heel at the stance phase of foot reaches to the ground and is finished when the heel reaches on the ground again in the next cycle. The distance between two heels is furthest at the start and finish stance positions. This procedure will collect 100% of the gait cycle. In order to robustly identify a person's gait signature, now there is a need to device the method for extracting gait cycles from a continuous signal of walking data [29].

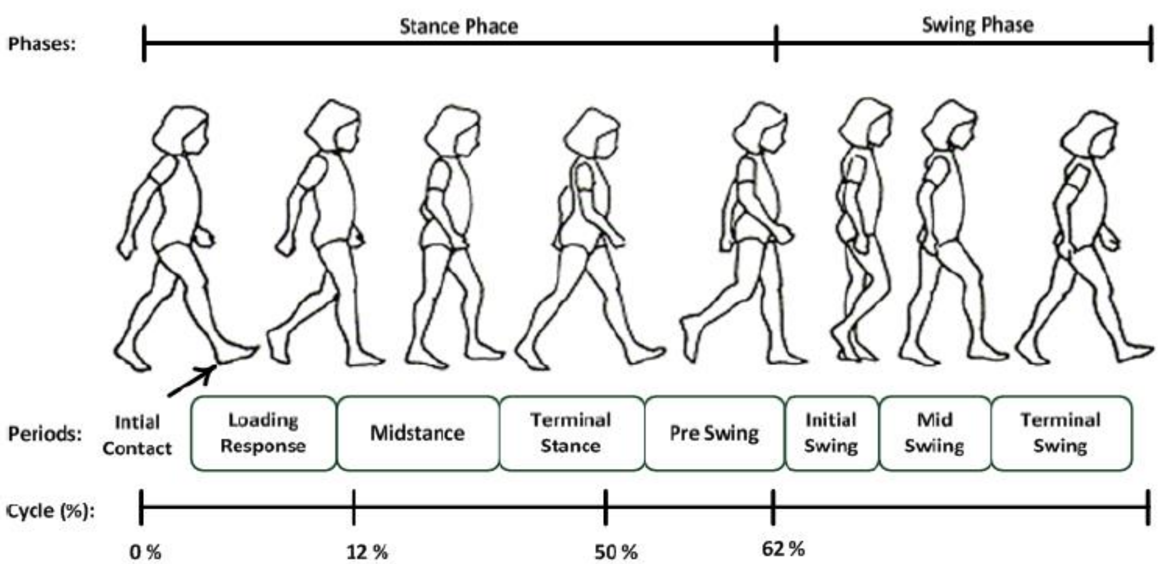


Figure 3.2 Gait cycle estimation [29].

For the propose of gait cycle estimation, the gait cycle can be defined as the time interval between two successive motions of one of the repetitive events of walking. Figure 3.3 shows steps of gait cycles utilized to identify major events during the stance and swing gate phases.

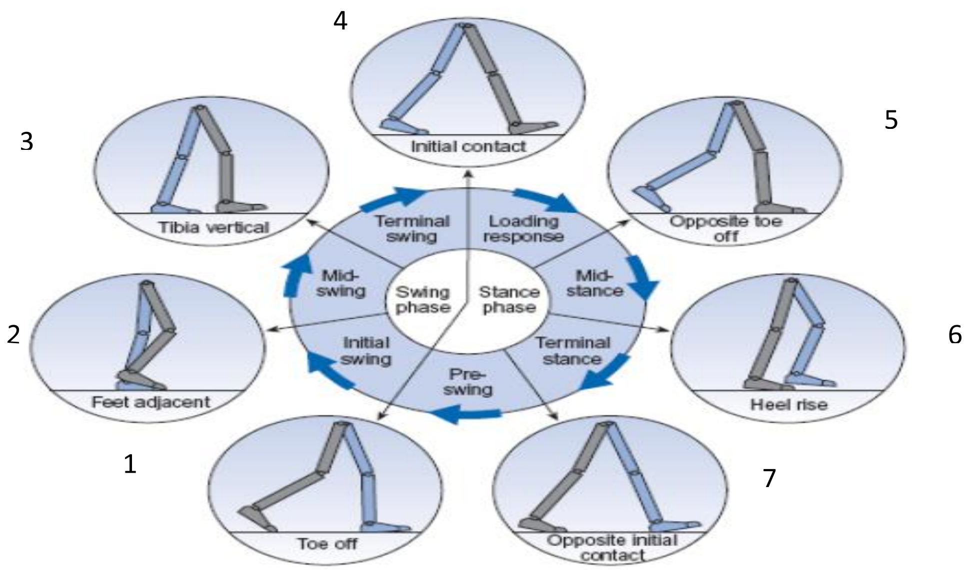


Figure 3.3 Events during gait cycles [30]

(Swing Phase: 1.Toe off. 2.Fee adjacent. 3.Tibla vertical. 4.Initial contact. Stance Phase: 5.Opposite toe off. 6.Heel rise. 7.Opposite iitial contact.)

As shown in Figure 3.3 the swing and stance phases of the event are subdivided into seven phases, four of which occur in the stance stage when the foot is on the ground, and three in the swing stage when the foot is moving forward through the air.

Through the swing stage on the left side, only the right foot is on the ground, getting a phase of right single support (or 'single limb stance'), which at the last point of initial contact by the left foot. There is then another phase of double support, until toe off on the right side. Left single support matches to the right swing phase and the cycle end with the next initial contact on the right. In each double support stage, one foot is forward, having just landed on the ground, and the other one is backward, being just about to leave the ground. The leading leg is in loading response, ‟sometimes represented to as ‘breaking double support’, ‘initial double support’ or ‘weight acceptance’. The trailing leg is in ‘pre-swing’, as well to known as ‘second’, ‘terminal‘or‘thrusting’ double support or ‘weight release’[30].

The stance stage although known as ‘support phase’ or ‘contact phase’, lasts from initial contact to toe-off. Right initial contact occurs at the time the left foot is still on the ground and there is a during of double support (also known as ‘double limb stance’) between at the beginning of contact on the right and toe off on the left.

3.2 Feature Extraction

The feature extraction is an important process in the area of image processing. Feature extraction is the process which includes a set of features, or image characteristics that will most efficiently or meaningfully represent the information for analysis and classification. Feature extraction techniques are supported in various image processing applications e.g. character recognition, they show its importance in phases of data storage which increases efficiency in classification and obviously in time consumption. The feature extraction techniques are applied to provide features that will be useful in classifying and recognition of images.

Before starting to this process, various image preprocessing techniques like by linearization, threshold, resizing, normalization etc. are applied on the sampled image. Gait feature recognition is performed in two steps: Model-Based Approach and Model Free Approach [31].

3.2.1 Model-Based Approach

Model-based gait recognition approaches converge on improving the structural model of human motion, and the gait patterns are then generated from the model parameters or tracking body components such as limbs, legs, arms, and thighs. Gait signatures used from these model parameters are employed for identification and recognition of an individual. It is evident that model model-based approaches are view-invariant and

scale-independent. Figure 3.4 shows the components of typical model-based approach of gait recognition system after capturing image videos [19]. The process for final classification follows comparison of the database image with gait signature (feature).
Figure 3.4 shows the various representation of the human body. Models used are usually stuck representations either surrounded by triangles or square or blobs, etc... The models include kinematical and physical constraints. For example, we can place on the model maximum variant angle of the knee joint.

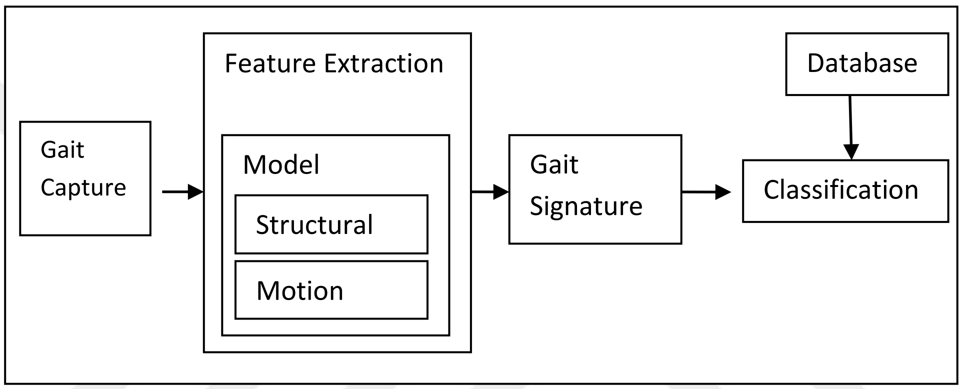


Figure 3.4 Component of a typical model-based gait recognition system

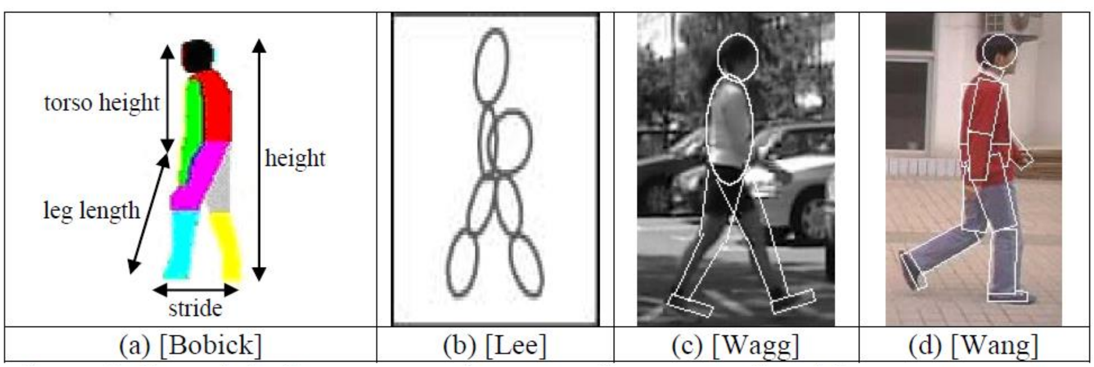


Figure 3.5 Example body parameters that are used in structural models [1][19].

The advantages of a model-based approach are that it can reliably handle occlusion (especially self-occlusion), noise, scale and rotation well, at the same time opposed to silhouette-based approaches. They also support to reduce the dimensionality required to represent the data.

The disadvantage of a model-based approach is its sensitivity to cloth and appearance changing. Further, implementing a model based approach shows also another disadvantage of high computational costs, due to the complex matching and searching to be performed..

We have many techniques in model-based feature extraction used in gait recognition and gender classification: A dynamic feature extraction of the human body is proposed in the reference [32]. In this technique two different triangles are formed (Figure 3.6). They are based on three points for one triangle; one hand , left toe feet and right toe feet, and for the second triangle; one hand, left heel feet and right heel feet. Intersection of these two triangles produced a new triangle for different gait cycles. The mean value of angles and intersection points are computed, and the results are compared to the features that are stored in the database for recognition purposes. This technique is not suitable for real time application.

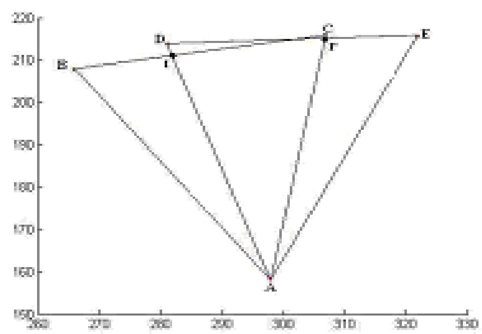


Figure 3.6 Gait recognition based on intersection point between two triangles

Another method is proposed in the reference [32], which is also based on the dynamic feature extraction that creates one triangle based on the three points (Figure 3.7). The first point is one hand of the human silhouette, and the next two points are the center of left and of right feet. The mean values of angles, computed for each gait cycle are used to compare results with the stored feature database.

The disadvantage of this technique is that we can use only two angles instead of using three, this is because if we know two of triangles, the third one will be known (Figure 3.6).

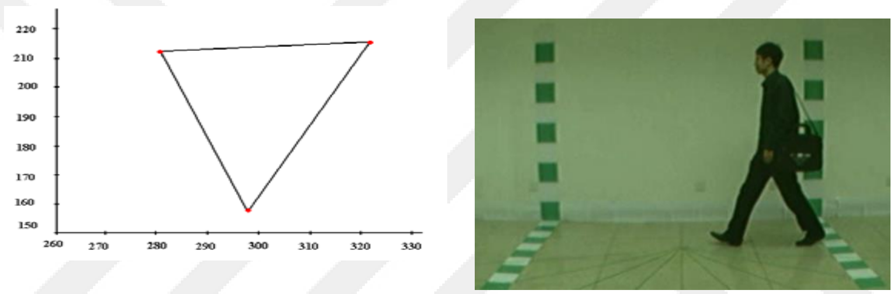


Figure 3.7 Gait recognition based on one triangle

Extracting features based on the four body points (palm, knee, ankle and toe.) was proposed in the reference [33]. This technique generates 16 nodes in for frames (Figure 3.8), depending on these four points at each phase of human walk. The weights are generated by Euclidian distance. The distance value of the current frame and the database frames are used for recognition purpose (Figure 3.7).

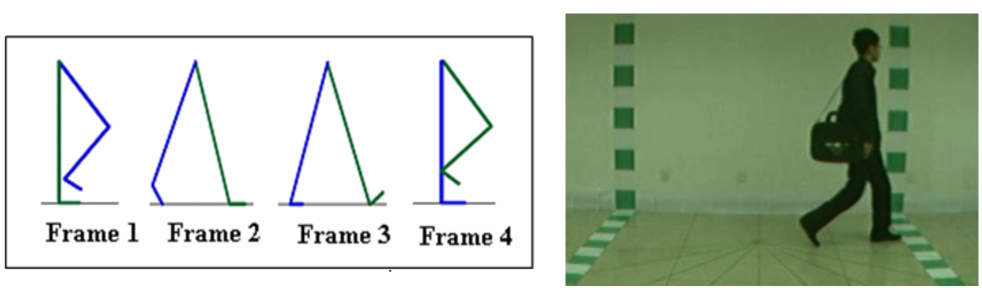


Figure 3.8 Bezier Curves [33].

3.2.2 Model-Free Approach

Model-free approaches make not try to recover a structural model of human motion. The features used for gait recognition contains; instant of shape, height and stride/width, and other image/shape templates. Gait Energy Image (GEI) represents the gait features in multiple silhouettes of a person over a gait cycle in a single image frame. GEI is the best feature for gait recognition and classification [34], which is defined as

$$G(x,y) = \frac{1}{T}\sum_{t=1}^{T} I(x,y,t) \tag{3.2.1}$$

where T is the number of frames in the sequence $I(x,y,t)$ is a binary silhouette image at frame t, x, and y are the image coordinates.

As shown in Figure 3.9, GEI reflects major shapes of silhouettes and their changes over the gait cycle. We represent it as gait energy image because; (a) each silhouette image is the space-normalized energy image of human walking at this time; (b) GEI is the time-normalized accumulative energy image of human walking in the complete cycle(s); (c) a pixel with higher intensity value in GEI means that human walking occurs more frequently at this position (i.e.with higher energy) [35].

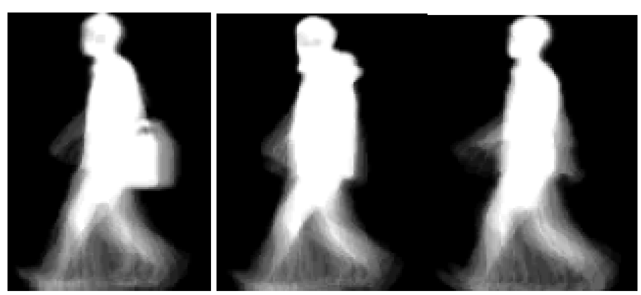


Figure 3.9 Motion Based Feature Exracted image after applying the Gait Energy Image algorithm.

Although Gait Energy Image (GEI) provides the average of the silhouettes of an image, pixel values of a silhouette can be captured with the method of **Gait Entropy Image (GEnI),** it is based on computing entropy pixel values of a silhouette captured randomly over a complete gait cycle. Dynamic body regions (e.g. legs and arms), which undergo consistent motions during a gait cycle, will lead to high gait entropy values, whereas those areas that remain static (e.g. torso) would give rise to low values. GEnI is computed from normalized silhouettes by performing first, extraction of silhouettes from each image frame using background subtraction [36], and second, normalizing the height of the silhouettes which is followed by the center alignment. Gait cycles are estimated using the maximum entropy estimation method in the lower half of the image. Given a gait cycle of image silhouettes which is sized, normalized and center aligned, a GEnI is computed by calculating Shannon entropy for each pixel in the silhouette images. Shannon entropy measures the uncertainty associated with a random variable. Assuming the intensity value of the silhouettes at a fixed pixel location as a discrete random variable, the entropy of this variable over a finshed gait cycle can be computed using GEnI function which is defined [37] as:

$$H(x,y) = -\sum_{k=1}^{k} P_k(x,y) log_2 P_k(x,y) \tag{3.2.2}$$

where *x,y* are the pixel coordinates and $P_k(x,y)$ is the probability that the pixel takes on the *k*-th value. In our case the silhouettes are binary images and we thus have k=2. A Gait Entropy Image *G(x,y)* can then be obtained by scaling and discretizing *H(x,y)* so that its value ranges from 0 to 255 as follows.

$$G(x,y) = \frac{(\mathrm{H(x,y)} - \mathrm{H_{min}})*255}{\mathrm{H_{max}} - \mathrm{H_{min}}} \tag{3.2.3}$$

where H_{min} = min(H(x,y)) and H_{max} = max(H(x,y)). While Gait Entropy Image is computed using the frames in a complete gait cycle there is no temporal alignment problem [37].

Figure 3.10 Gait Entropy Image

Figure 3.10 shows that the dynamic region of the human body, including legs and arms which undergo motions in relation to other body parts, are represented by a higher intensity value the GEnIs . This is because silhouette pixel values in the dynamic regions are more uncertain and thus more informative leading to higher entropy values. In difference, the static areas such as torso give rise to low-intensity values.

3.3 Wavelet Transformation

Discrete wavelet transform (DWT) is the best tool for image processing and computer vision such us used for compression, detection, recognition silhouette image. Wavelet has adaptive features of space-frequency localization and multi resolutions. The basic reasons for WTs popularity lie in its complete theoretical framework, the high flexibility of choosing basic and the low computational complexity [38].

If $L^2(R)$ represent the vector space of a measurable, square integrable, one-dimensional (1-D) function, the continuous wavelet transform of a 1-D signal $f(t) \in L^2(R)$ is defined as:

$$(W_a f)(b) = \int f(t) \emptyset_{a,b}(t) dt \tag{3.3.1}$$

where the wavelet function $\emptyset_{a,b}(t) \in L^2(R)$ can be expressed as a function of time as

$$\emptyset_{a,b}(t) = a^{-\frac{1}{2}} \emptyset \left[\frac{t-b}{a}\right] \tag{3.3.2}$$

where the variables *a* and *b* are the scale and location parameters, These basic functions are called wavelets and they have at least one vanishing moment. The oscillation in the basic functions increases with a decrease in a . Equation (3.3.1) can be discrete by restraining a and b to a discrete lattice ($a = 2^n$, $b \in Z$). Typically, there are some more constraints on a when no redundant complete transform is implemented and a multi resolution representation is pursued. The wavelet basic functions in Eqution (3.3.2) are dilated and translated versions of the mother wavelet $\emptyset(t)$ [38] because the wavelet coefficients of any scale (or resolution) should be computed from the wavelet coefficients of the next higher resolutions. Wavelet transformation decomposes the images somehow Any decomposition of an image into wavelet involves a pair of waveforms: The high frequencies relating to the detailed parts of an image and the low frequencies relating to the smooth parts of an image [39].

DWT for an image as a 2-D signal can be derived from a 1-D DWT. corresponding to the feature of the DW decomposition, an image can be decomposed to four sub-band images through a 1-level 2-D DWT, (Figure 3.11). These four sub-band images can be mapped to four sub-band elements representing LL “Approximation”, HL “Vertical”, LH “Horizontal”, and HH “Diagonal” .

Second level of decomposition can then be conducted on the LL sub band. Fig 3.12 shows a two-level wavelet decomposition of two images of size (112x92) pixel **[38].**

The image shown on left frame Figure 3.11 decomposed into its approximations when DWT is applied to LL1 . The second time application of DWT produces 4 subband symbolically LL2 with approximate coefficient HL2 for Vertical, LH2 coefficient for Horizontal and HH2 coefficient for Diagonal approximation..

In the wavelets transformation, one can analyzes low-frequency components (LL) of the image signal with high frequency resolution, although at the same time showing at high-frequency components (HL, LH and HH) with high time resolution.

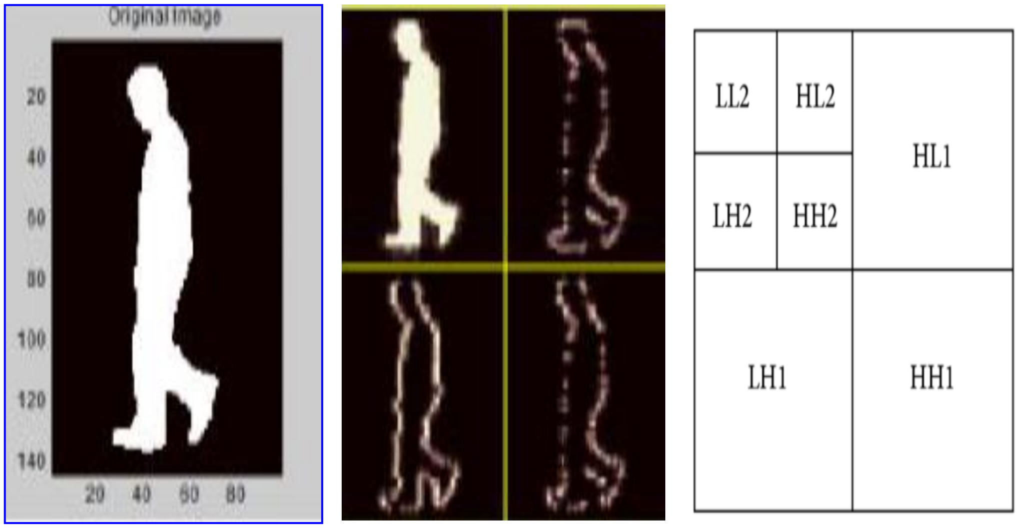


Figure 3.11 Images obtained after wavelet transformation [39]
(a) LL2: Approximation. (b) LH2: Vertical. (c) HL2:Horizantal (d) HH:Diogonal

Nastar et al. [38] had also investigated the relationship between variations in facial appearance and their deformation shadow .They found that facial expressions and small incidents affect the intensity manifold locally. Under frequency-based representation, the only high-frequency shadow is affected, called high-frequency phenomenon. Moreover, changes in pose or scale of a face affect the intensity various globally, in which only their low-frequency shadow is affected, called low-frequency phenomenon Lai et. al. [11] worked on the effects of improvement combining Wavelet Transformation with Eigenface vectors:

1) The effect of opposite facial expressions can be reduced by removing the high-frequency components.
2) The low-frequency components only are sufficient for recognition.

As explained in the following sections in the present investigation we will mainly use low-frequency sub band coefficients for recognition to reduce a natural difference in the images of the same person. Further, decomposition of the image to the LL subband (two-level decomposition), guides to lower dimensionalities and a multi-resolution image. We could observe the effects of higher level decomposition, like three or four level even higher decompositions [40]. The advantage of Wavelet Transformation is its uniqueness for multi-resolution analysis. It is the time-frequency localization analysis which has the capability of local features in the time domain and frequency domain.

3.4 Classification

The classification is the last step of gait recognition. The classification method is a behavior validity that can be made under specify scenario. In order to identify people movement in an intelligent security monitoring system, the object in the image is subjected to preprocessing first by performing background subtraction, boxing the boundary around the object, then feature extraction and latter classification.

3.4.1 k-Nearest Neighbor (k-NN)

In pattern recognition or classification the nearest neighbor algorithm is one of the simplest machine learning algorithm. It is a non-parametric technique, the k-nearest neighbor algorithm is a technique for classifying objects based on nearest training examples in the problem space. k-NN is a type of instance-based learning, where the function is just approximated locally and all computation is deferred until classification. We should compute absolute distance by measuring the distance of feature vectors using Eq. (3.5.1) for some distance function d(x,y) [41].

$$L_1(x,y) = \sum_{i=1}^{N} |x_{i-}\ y_i| \tag{3.5.1}$$

where x , y are vectors of image scenarios composed of N features, such $x=\{x_1,\ldots..x_N\}$ and $y= \{y_1,\ldots\ldots.y_N\}$

The object is classified by a majority elect of its neighbors, with the object being assigned to the class most common midst its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply occupied by the class of its nearest neighbor. An object is classified by the distance from its neighbors, with the object being occupied to the class most common among its k distance nearest neighbors. To compute distances of all training vectors to test vector,any of the following distance computing methods such as Euclidean distance, City block distance, Cosine distance, and Hamming distance can be used. With the help of k-nearest neighbor, classifier computation take place between extracted train features vector and test feature vector [42]. Figure 3.12 shows a sample of meaning distance between the object and its k-NN nieghbors

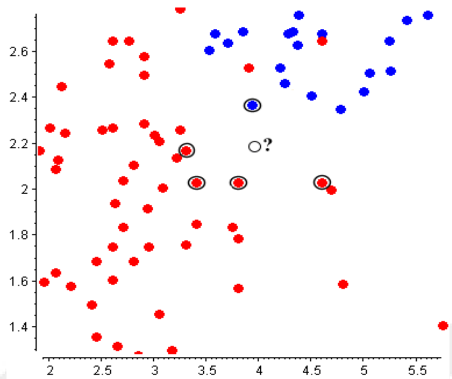


Figure 3.12 k-NN sample

3.4.2 Support Vector Machines (SVM's)

An SVM is a linear or non-linear classifier, it is a mathematical function that can distinguish two different kinds of objects. Support Vector Machines (SVMs) being a class of supervised learning algorithms was first introduced by Vapnik [43].SVM provides a set of identity training vectors (positive and negative input examples), then SVMs learn a linear decision boundary to discriminate between the two classes.

Classification is achieved by realizing a linear or non-linear separation exterior in the input space. In Support Vector classification, the separating function f(x) can be expressed as a linear combination of kernel $K(x_j,x)$ functions associated with the Support Vectors S ∈ (xj, yj) [44].

$$f(x) = \sum_{x_j \in S} \alpha_j \, y_j \, K\left(x_j, x\right) + b \qquad (3.4.2)$$

where x_i assume the training patterns, $y_i \in \{+1, -1\}$ assumes the corresponding class labels and S assumes the set of Support Vectors $b \in R$, where R is the set of real numbers. Figure 3.13 shown the classification achived after applaying SVMs on a sample image data

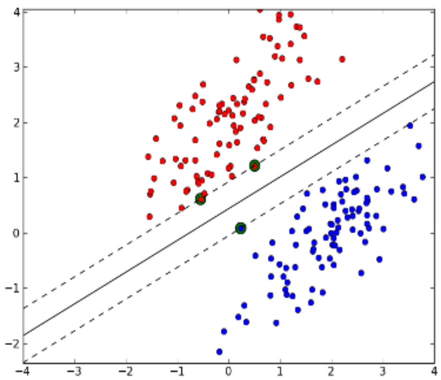


Figure 3.13 Support Vector Machine [44].

CHAPTER 4

GENDER CLASSIFICATION USING NEUTRAL AND NON- NEUTRAL GAIT SEQUENCES

4.1 The proposed method

In this thesis we propose the method of gender classification which is based on human gait features. As we mentioned before (in chapter one) human gait challenges are divided into two factors: External and Internal factor. In this method we investigate two types of external factors (bags and coats). For the present computations for classifications we use CASIA B gait dataset since it is recognized as the largest and widely used database in gait-based gender classification methods.

The method being developed is based on three main steps (Figure 4.1). The first step is preprocessing all the videos of CASIA database. In this database each video contains a single individual walking in a certain view direction. The selected viewing direction in our proposed method is 90 degree (i.e. side view), which contains more dynamic information about human gait.

As shown in Figure 4.1 the videos were pre-processed by applying a background subtraction method to generate the silhouettes. We used frame difference method to compute the difference between consecutive frames and frame references. To generate the frame reference we compute the average of the first ten frames assuming that there is no object on the scene. Applying box boundary to the frames obtained after gait cycle estimation Normalization and alignment processes were applied to each silhouette image as a final process of this step.

As shown in Fifure 4.1 this is the second step to perform feature extraction. The gait feature sets in this method are based on Wavelet Transformation and Gait Entropy Energy Image (GEnEI). In this method three feature vectors have been produced; the first feature vector is extracted from LL2 wavelet subband by applying GEnEI method first on the sequence of frames during one gait cycle, which is called Approximation coefficient Gait Entropy Energy Image (AGEnEI). The second feature vector is extracted from LH2 subband by again applying GEnEI method, which called Vertical coefficient Gait Entropy Energy Image (VGEnEI). The last feature vector is constructed from The first and second feature vectors of the human body are divided into two parts Upper and Lower body using on golden ratio proposition (Upper body = 0.62 × height, Lower body = 0.32 × height), and then for this feature for the upper body part of the silhoute image frame we apply Vertical coefficient and for the lower body part we use Approximation coefficient, then GEnEI applied to both frames of the body parts to generate the image of the human body model. This feature called Approximation and Vertical coefficients Gait Entropy Energy Image (AVGEnEI). After achiving AGEnEI , VGEnEI and AVGEnEI feature vectors, each of them were tested separately and then they were fused at decision level for final classification.

At third step of the process we applied k-Nearest Neighbor (k-NN) and SVM classification methods separately for the final classification. To test the proposed method we used CASIA B gait database which contains 124 subjects (93 males and 31 females).

Basic computational steps of the proposed gender classification is given in the form of flow chart in Figure 4.1 and computational procedure followed in each step is explained in Figure 4.2.

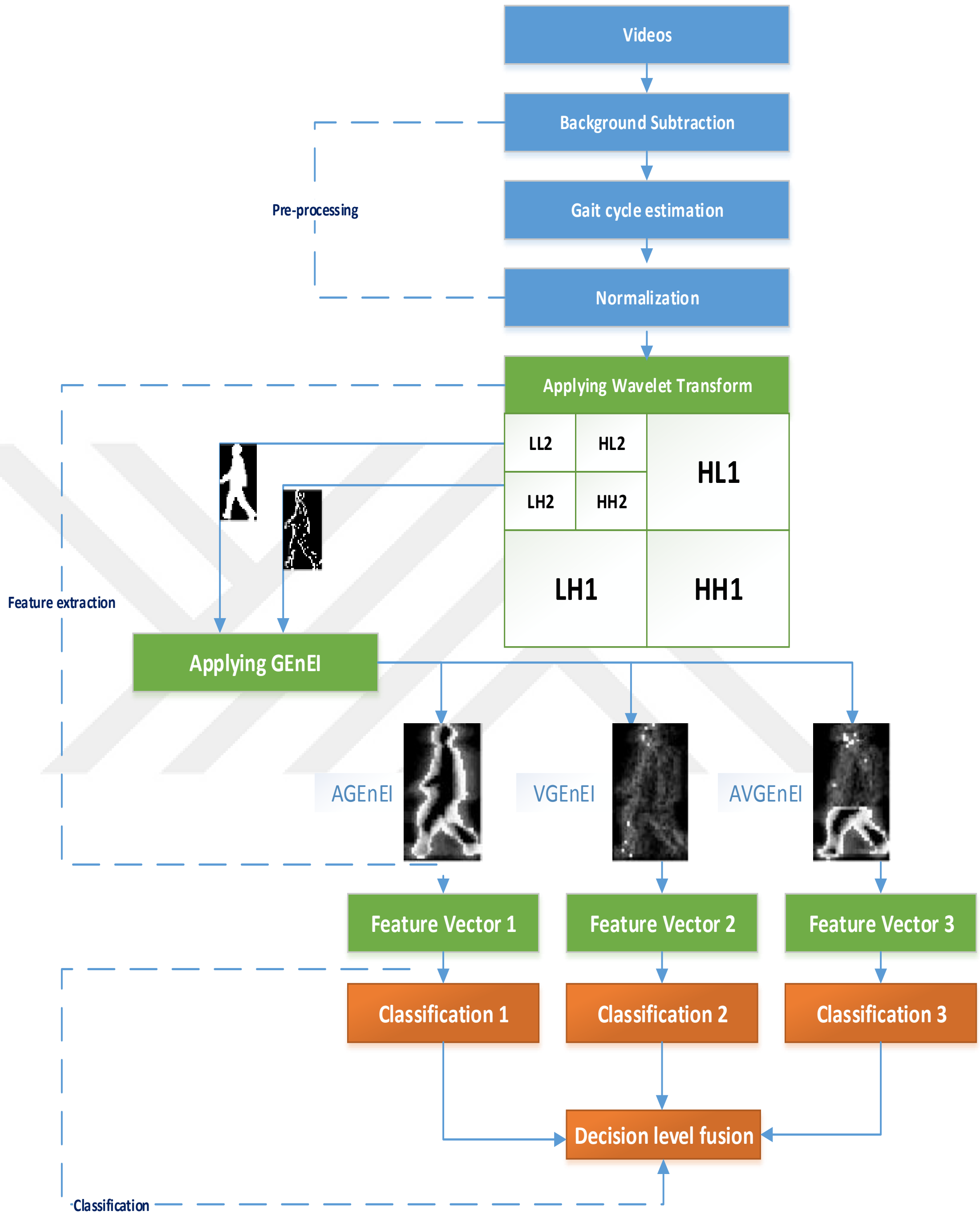


Figure 4.1 Overview of the proposed gender classification method

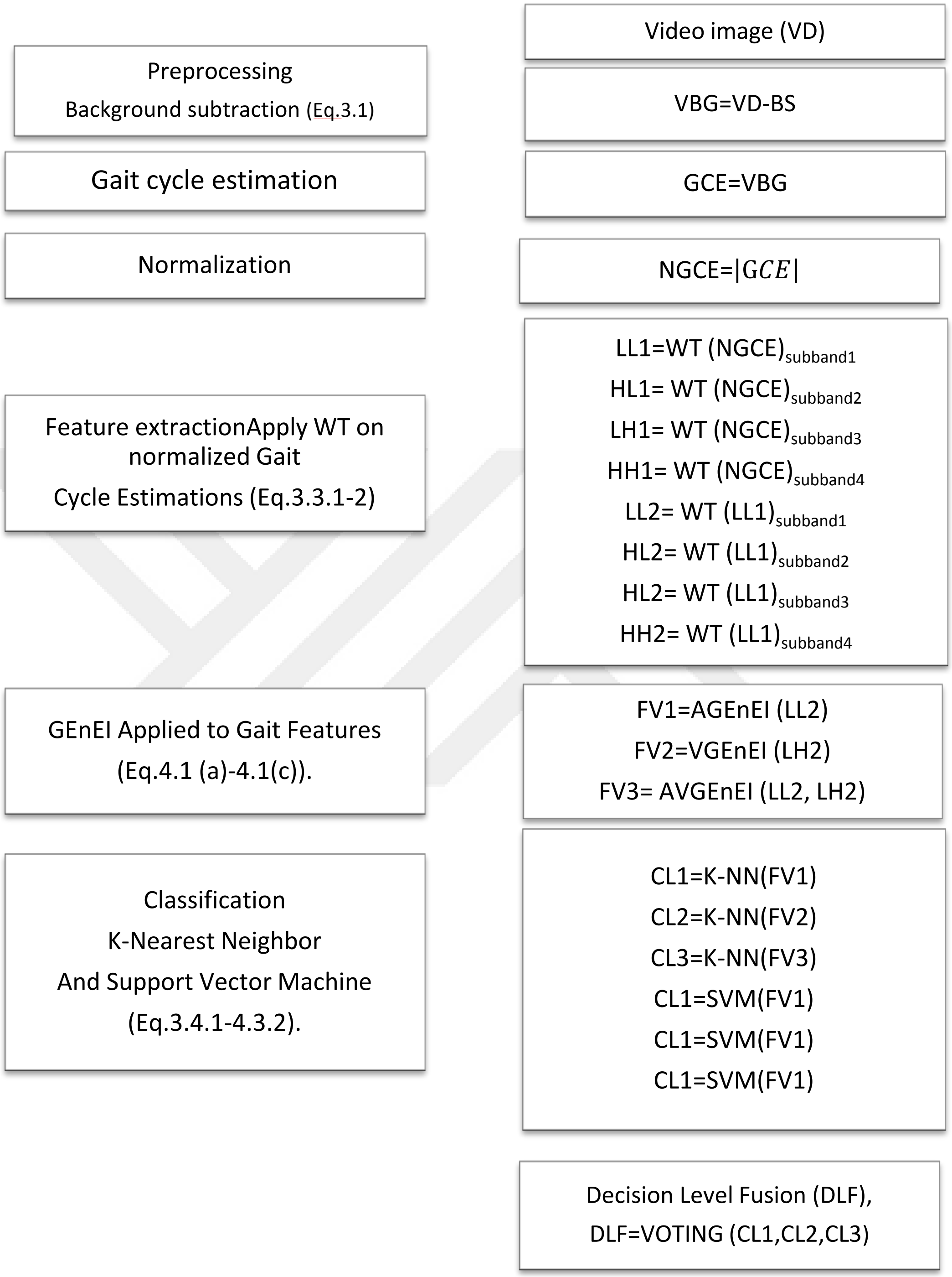


Figure 4.2 Computational steps followed for the proposed gender classification algorithm given in Figure 4.1

4.2 Gait Entropy Energy Image (GEnEI)

GEI and GEnI are two methods that are widely used in the literature as a gait feature recognition.This is because of their simplicity and effectiveness [34] and [45]. The limitations of GEI and GEnI are the lacking of robustness to deal with covariate conditions which affect the static areas of human body. Although GEnI is better than GEI in dealing with such problems, because GEnI reduces the effect of static parts that are influenced by bag and coat, but still both are not enough to provide good performance especially in Coat Wearing (CW) gait sequences.

Usually, each of GEI and GEnI are obtained from the spatial domain of the sequence of frames during one gait cycle. In this thesis we propose a new gait feature based on wavelet transform called Gait Entropy Energy Image (GEnEI). This feature is constructed as based on GEI and GEnI. First, we compute GEI, then we check each pixel value in the constructed GEI whether the pixel value is less than 0.5 and greater than 0. We use the value of GEI in GEnEI, otherwise we use the value of GEnI in GEnEI.

$$GEI(x,y) = \frac{1}{T}\sum_{t=1}^{T} I(\mathrm{x,y,t}) \qquad (4.1(a))$$

$$\mathrm{GEnI}(x,y) = -\sum_{\mathrm{k=1}}^{\mathrm{k}} \mathrm{p_k}\,(\mathrm{x,y}) \log_2 \mathrm{p_k}\,(\mathrm{x,y}) \qquad (4.1(b))$$

$$\mathrm{GEnEI}(x,y) = \begin{Bmatrix} GEI(x,y) & if\ GEI(x,y) > 0\ and < 0.5 \\ GEnI(x,y) & Otherwise \end{Bmatrix} \qquad (4.1(c))$$

where *T* is the number of frames in the sequence *I(x,y,t)* is a binary silhouette image at frame *t*, *x* and *y* are the image pixel coordinates, and $P_k\,(x,y)$ is the probability that the pixel takes on the *k*-th value.

In this thesis three feature vectors are constructed from GEnEI using wavelet transformation method. For our purpose Level 2 was seleceted to process three feature vectors: the first feature vector based on Approximation coefficient subband is called AGEnEI, the second feature vector based on Vertical coefficient subband is called VGEnEI and the last feature vector called AVGEnEI,. To construct the last feature, we divide the human body into two parts as upper and lower body. For the upper body part we use VGEnEI and for the lower body part we use AGEnEI. This division was made to reduce the effect of bags and coats that mostly changes the image of the upper body part.

4.3 Implementation of CASIA Database

CASIA B Gait database was used through out the prsent work. Due to imbalanced gender numbers in this database (93 males and 31 females), we selected a randomly equal subset of 25 males and 25 females of Neutral gait sequences (Nu) for the gallery set (see Appendix A for one video sequence). The gallery set was constructed from the Nu gait sequence only. The remaining records of Nu gait sequences are Coat Wearing (CW) and Carrying Bag (CB) gait sequences which are used as a probe set. The test was repeated 30 times to cover the entire Nu data that was used in the gallery. The accuracy rate is the average result of 30 repetitions. See Appendix B for computing average fusion level for classification. The classification was performed using 10-Fold Cross Validation (FCV) for k-NN and SVM. .

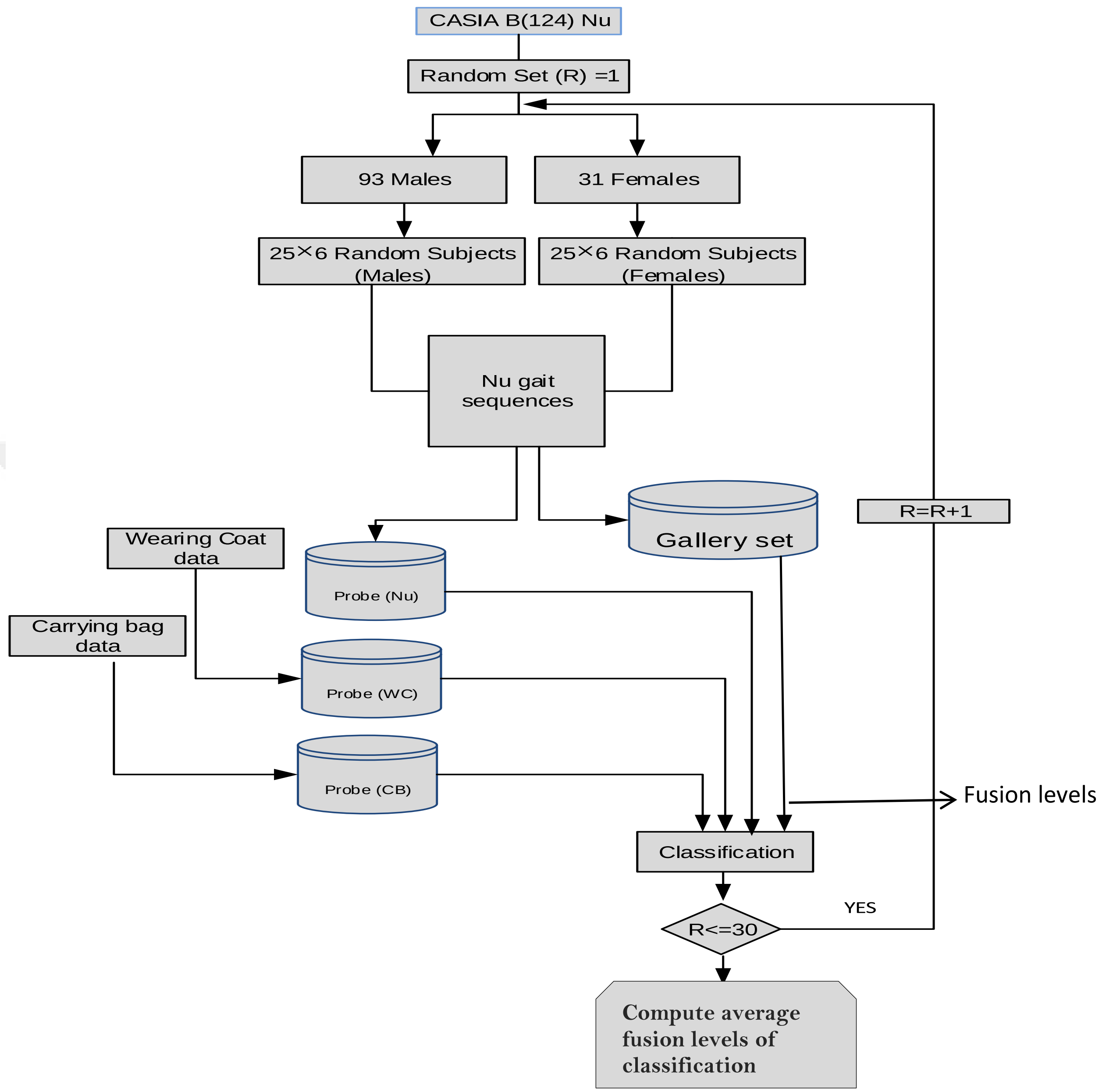


Figure 4.3 Generating gallery and probe set from the CASIA B for gender classification.

4.4 Results and Discusion

We tested the performance of the proposed method by presenting the result of three feature vectors separately and fusing them using the decision level fusion method. These tests are based on two different classification methods namely k-NN and SVM, and both of them are used separately to test the performance of the proposed method. In all tests 10 fold cross validation was applied to separate the gallery and probe set. Figure 4.3-4.5 indicated the flowchart of computation for fusion levels applied in classification.shows the results of the proposed method using k-NN with (k= 1, 3, and 5). These results represent the average and standard deviation of the 30 repeated experiments.   Figure 4.3 presents the results using k-NN with k=1. The result shows that for Nu gait sequence AGEnEI provides better results compared to VGEnEI and AVGEnEI.This is because approximation coefficient subband provide similar information as the original spatial image . Also the gallery and probe set contain the same gait sequences variation (Nu gait sequences). In the case of having different gait sequences in the probe and gallery set the test result show that VGEnEI provides better results for CB while for CW again AGEnEI provides better result compared to the other sets of features. The reason behind these result is that GEnEI originally reduced the effect of coat that is why AGEnEI provided better result, while the effect of bag is still remain on the human body after using GEnEI, therefore VGEnEI which is based on the vertical subband only provides better results compared to other two feature sets.

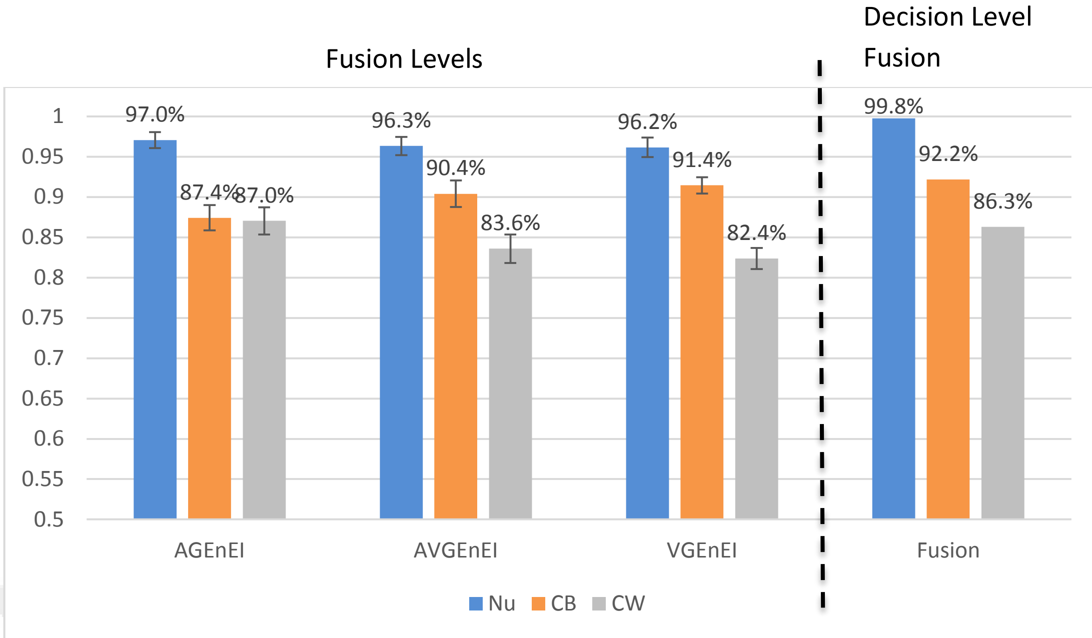


Figure 4.4 The fusion levels and their averages obtained with 1-NN (k=1),for each (Nu Neutral, Carrying Bag (CB) and Coat Wearing (CW).

In figure 4:4 we present the fusion level fusion and their averages using k-NN with k=3; the test results show that for Nu and CB cases the results are below what provided with k=1 for each of AGEnEI, VGEnEI and AVGEnEI with one exception (AGEnEI in CB case), while for CW the results are better than k=1 in the case of using AVGEnEI .

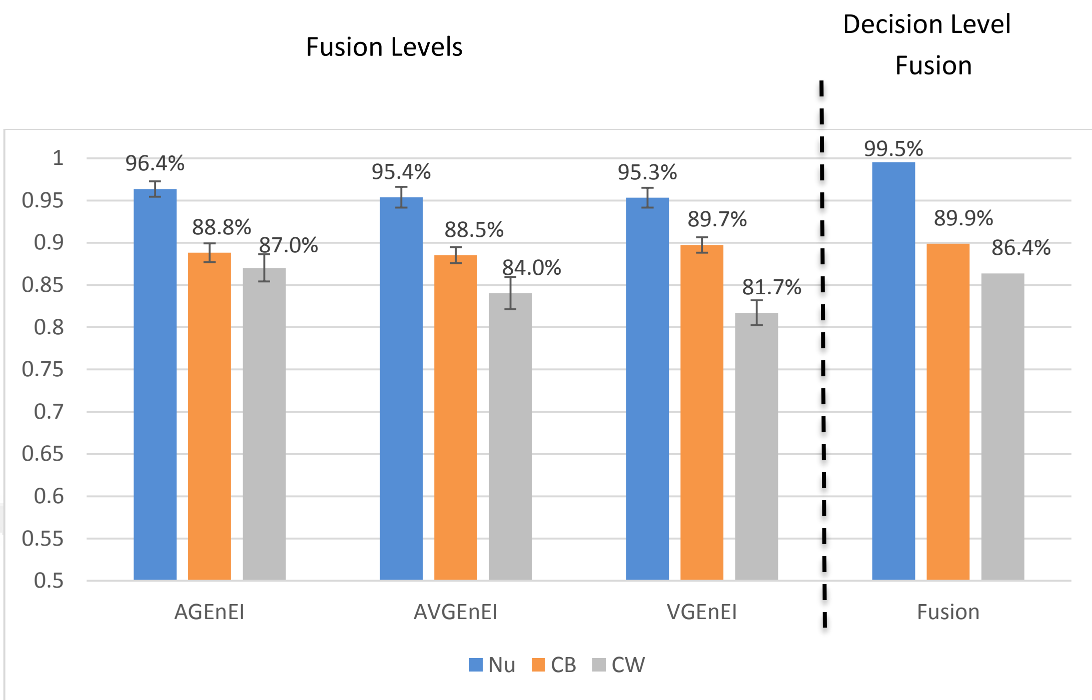


Figure 4.5 The fusion levels and their averages obtained with 3-NN (k=3),for each (Nu Neutral, Carrying Bag (CB) and Coat Wearing (CW).

Figure 4.5 present the fusion levels and their averages for gender classification using k-NN with k=5. The test results shows that in all of the case the results achieved using k=5 are below what achieved by k=1 and k=3 with two exceptions (AGEnEI and VGEnEI in CW).

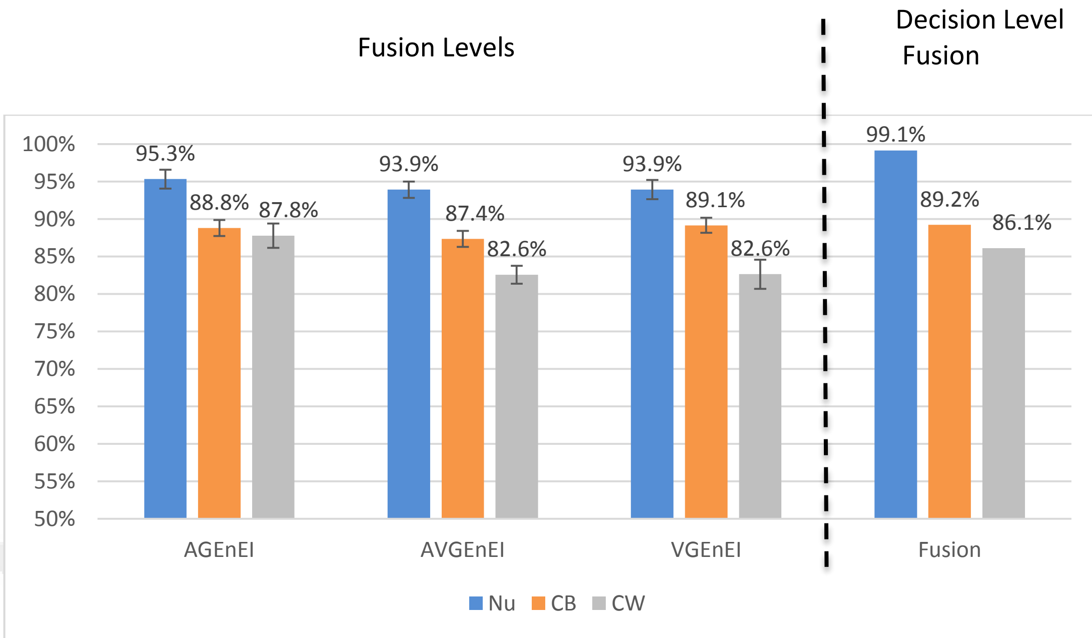


Figure 4.6 The fusion levels and their averages obtained with 5-NN (k=5),for each (Nu Neutral, Carrying Bag (CB) and Coat Wearing (CW).

Elobarateing the results obtained with k=1, 3 and 5, we conclude that k=1 providess better fusion levels compared to those achived with k=3 and 5, and the decision level fusion is better than using each of the feature set separately in all of the cases. In the next experiment we test the performance of the proposed method using SVM.

The result of figure 4.4 to 4.6 are summerized in Table 4.1 for classification 1-NN (k=1). Also in Table 4.2 comparative results of the prsent work to those obtained tn the liturate are displaied

We use the same feature sets that were used previously, instead of using k-NN as a classification method we use SVM as a binary classification method (see Figure 4.7). First each of the feature set was tested separately, then decision level fusion method was used to fuse the three feature sets (AGEnEI, VGEnEI, and AVGEnEI). The results show that Nu gait sequences provide better than results compared to CB and CW. For Nu case AGEnEI which 97.3%, which is better than VGEnEI and AVGEnEI that which are 96.7% and 94.4% respectively. For CB the results are below what we achieved by Nu case.This is because in the gallery set we use Nu gait sequences only. Due to the effect of bags on human body AGEnEI and AVGEnEI result in fusion levels of 66.7% and 66.3% respectively, while with VGEnEI it is 78.9% which is better compared to other two sets, this is because this feature set is based on the vertical coefficients only. In the case of CW the result are relatively better than CB for each AGEnEI, AVGEnEI, and VGEnEI which provides fusion level of 76.2%, 81.2% and 83% respectively. The decision level fusion in these test lead to increase the result in Nu gait sequences, while for CB and CW the results are lower compared to VGEnEI.

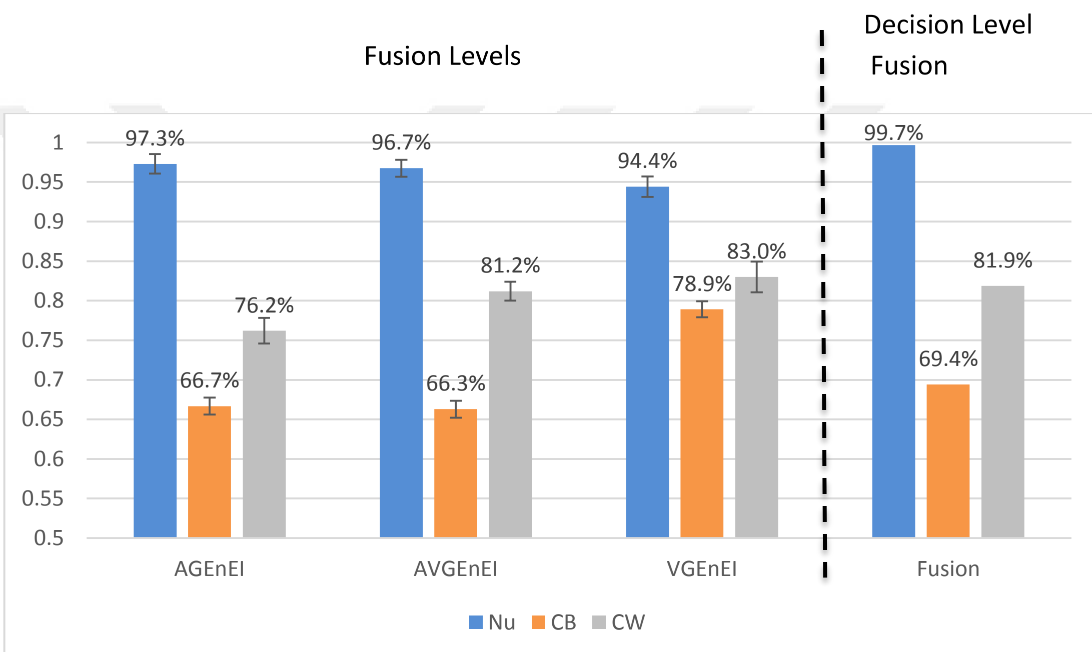


Figure 4.7 The results of decision level fusion method using SVM, for each of Nu normal, CB Carrying Bag and CW Coat Wearing.

To indicate effectiveness of the classification methods of we compare the obtained with the methods result k-NN and SVM. Table 4.1 shows the results achieved with SVM and k-NN using each of AGEnEI, AVGEnEI and VGEnEI feature sets and their fusions. The test results show that for Nu gait sequences SVM provide better result for each of AGEnEI and AVGEnEI, while VGEnEI decision level fusions, k-NN for k=1 is better than SVM.

CB and CW gait sequences k-NN (k=1) provides better results than SVM except in the case of using VGEnEI feature sets. The reason behind this test are that in Nu gait sequences the gallery and probe set contain the same type of gait sequences (Nu gait sequences), thus in VGEnEI some necessary information are removed, due to using vertical subband only, while in CB and CW the galley and probe contain different gait sequences, thus bags and coats affect the results negatively, in this case VGEnEI provide good results because it removes the information is the result of SVM bags and coats.

Table 4.1 Comparsion of the proposed the methods using k NN (k=1) and SVM

k-NN (k=1)	AGEnEI	AVGEnEI	VGEnEI	Fusion
Nu	97.0%	96.3%	96.2%	99.8%
CB	87.4%	90.4%	91.4%	92.2%
CW	87.0%	83.6%	82.4%	86.3%
SVM				
Nu	97.3%	96.7%	94.4%	99.7%
CB	66.7%	66.3%	78.9%	69.4%
CW	76.2%	81.2%	83.0%	81.9%

Now we shall compare our result with those published in the literature. In the process of comparison we selected the proposed gender classification in neutral and non-neutral cases and of CASIA B gait database. It can be seen that our scheme outperform the two other scheme in the case of Nu and CB. Although in the case on CW the result achieved with our proposed method is below the result of the reffrence, however the result of the average of three cases (Nu, CB and CW) shows that our proposed method outperform the other two methods.

Table 4.2 Comparing proposed method with results published in the literature.

Methods	Nu %	CB %	CW %	Average %
Lee and Grimson[19]	---	---	---	**85.0**
Lu and Tan[46]	---	---	---	**87.99**
Proposed Method	99.8	92.2	86.3	**92.8**

CHAPTR 5

CONCLUSION AND FEATURE WORK

5.1 Conclusions

Recently, many researchers focused on biometric recognition/classification system for security purposes. Human gait identification/classification as a new biometric system aims to identify/classify people at a distance by the way they walk. However, as in the case of most biometric systems, gait recognition suffers from limitations and challenges, these challenges are classified into two factors; external factors like clothes, carrying objects and viewing angles, and internal factors such as pregnancy and gaining or losing weight etc..

(i) In the present work we investigated gait-based gender classification method using Neutral (Nu) and Non-neutral (Carrying Bags (CB) and Coat Wearing (CW) gait sequences. To extract human gait features we need to remove the background from their images We used frame difference method for computing the difference between the continuative frames with the frame references. To generate the frame reference, the average of ten frames were computed in order to achieve human images more accurately.

(ii) Different types of features are proposed in the literature for the purpose of gait recognition and gender classification. The mostly used feature sets are Gait Energy Image (GEI) Gait Entropy Image (GEnI). These two feature sets are extracted from the spatial domains of image pixels. In the present work we proposed a new feature set that were generated from GEnI and GEI and called Gait Entropy Energy Image (GEnEI). These feature sets were presented in three different forms based on Wavelet Transform technique, using approximation and non-approximation coefficients.

(iii) To construct the first feature sets, we used LL2 wavelet subband, by applying GEnEI method on the sequence frames during one gait cycle and called Approximation coefficient Gait Entropy Energy Image (AGEnEI). For the second feature set we used

LH2 subband as one of the high frequency non-LL subband called Vertical coefficient Gait Entropy Energy Image (VGEnEI). The idea behind this second feature set is that the human body is represented vertically and vertical subband neglects some information from the human body that mostly are affected by bags and coats. The human body feature provides static and dynamic information; the upper body mostly represents static information, while lower body provides dynamic information. To use the advantage of each, the third feature set is constructed from the first and second feature vectors by first dividing human body into two parts, upper and lower body part using the golden ratio proposition. Then, for this new feature derived for the upper body we used Vertical coefficient and for the lower body part we used Approximation coefficient, then GEnEI was applied for the resulted human body model. This feature called Approximation and Vertical coefficients Gait Entropy Energy Image (AVGEnEI). To test the performance of the proposed method, CASIA B gait database was used.

(iv) Two different classification methods were applied separately called k-NN and SVM for three feature sets (AGEnEI, VGEnEI and AVGEnEI) and these feature sets were tested separately and were fused using the decision level fusion method. In addition to Nu gait sequence database (gallery), CB and CW gait sequences were included in the probe set database to address the external factors challenging gait recognition. The test results obtained with k-NN (k=1) as a classification method showed that in the case of using Nu gait sequence as a test method, AGEnEI provided 97.3%, which is better than 96.7% and 94.4% that was achieved with VGEnEI and AVGEnEI, respectively. This is because of two reasons; first in the gallery set we used Nu gait sequences, while the probe and Nu gallery sets contain the same type of gait sequences, and second AGEnEI provides approximate results of a special domain. In the case of having different gait sequences in the probe and gallery sets, the test results showed that VGEnEI outperforms the other two feature sets with CB providing 91.4%, while CW outperforms the other two sets with AGEnEI producing 87%.

The tests were extended to use three different sequences of k (1, 3 and 5). The results showed that in most cases the sequence k=1 produces better results compared to the other k values.

When the method SVM was used, the tests showed that in the case of applying Nu gait sequence SVM provides fusion levels 97.3% and 96.7 with AGEnEI and AVGEnEI respectively. These results are better than those obtained with SVM for the same two feature sets using kNN, which provides the corresponding fusion levels of 97% and 96.3% respectively. However, SVM outperforms kNN with VGEnEI feature set by 1.8%.

Moreover, for CB and CW gait sequences k-NN (k=1) provided better accuracy than SVM except in the case of VGEnEI for CW, for which SVM outperforms kNN by 0.6%. The reasons behind these results are that in the gallery set we used only Nu gait sequences and the SVM were trained only on Nu gait sequences, however for the probe set tests were done on different gait sequences.

After combining three proposed feature sets (AGEnEI, VGEnEI and AVGEnEI) using kNN at the decision level fusion led to the highest accuracy in comparison to the case when each set of feature was tested separately. Furthermore decision level fusion based on SVM did not improve the results except in the case of Nu sequence.

5.2 Future Work

Presently, a large amount of research relating to gait-based gender classification being developed, but still there are challenges that need to overcome. In this master thesis we focused on two external factor challenges of gait feature (carrying bag and coat wearing). Here we list a few promising directions for our future work.

1. In this master thesis we proposed a new feature sets called Gait Entropy Energy Image for gender classification, in the near future we will use this feature for gait recognition, moreover we test the use of gender classification with gait recognition aiming to improve the performance of human gait identification system.
2. Few research works, including the current master thesis, used side view angle for gait-based gender classification. in real time scenarios you can guarantee human gait with specific view angle (direction) to be used in the gallery set, but you cannot guarantee the view angle of the human that you want to recognize his/her gait (the probe set), in future work we will focus on using different view angle for gender classification.
3. Kinect sensor is a new camera that originally designed for game applications, recently researchers used this camera for gait recognition and gender classification, Future investigations will also include using Kinect sensor for gender classification.

REFERENCES

[1] Liang Wang. (2009).*Behavioral Biometrics For Human identification:Intelligent Application*.: IGI Global.

[2] XuHan.(2010)."Gait Recognition Considering Walking Direction," USA,

[3] Rohit,Vinay Kumar Pathak and K.V.Arya Katiyar. (2013).*A study on existing gait biometric approaches and challenges*. International Jounral of Computer Science 135-144.

[4] Choon Boon,Yong HaurTay ,and Bok Min Goi. Ng.(2012).*Vision-based human gender recognition:A survey*. arXiv preprint arXiv, p1204-1611.

[5] Dario Maio,Anil Jain and Salil Prabhakar Davide Malton, *Handbook of Fingerprint Recognition*., Spring 2003.

[6] Acero A,Hon HW. Huang X .(2001).*Spoken Language Processing*.: Upper Saddle River,NJ:Pretince-Hall,Inc,

[7] J.Daugman. (2004).*"How iris recognition works"*.IEEE Transactions on circuits and systems for Video technology.

[8] StanZ.Li and Anil K.Jain, *Handbook of Face Recognition*., Spring,2005.

[9] M., Plamondon, R. Parizeu. (1990). " *A comparative analysis of regional correlating dynamic time warping, and skeletal tree matching for signature verification*".IEEE transactions on Pattern Analysis and Machine Intelligence, 12, pp. 710-717.

[10] A.K.Jain and K.V.Mardia N.Duta, (2002)."Matching of Palm Print," *Pattern recognition*, pp. 23(4):477-485, febreuary.

[11] Y. Wang, Z. Zhang and Y. Wang M. Hu, (2010)."Combining Spatial and Temporal Information for Gait Based Gender Classification"," *20th International Conference on Pattern Recognition*, pp. 3679-3682.

[12] J., Nixon, M.S. Yoo, (2011)."Automated Marker-less Analysis of Human Gait Motion for Recognition and Classification. ," *ETRI Journal 33(2)*, pp. 259–266 .

[13] A.F., Johnson, A.Y. Bobick, (2001)."Gait recognition using static activity-specific parameters. " *Proceedings of IEEE Computer Society Conference on Computer*

Vision and Pattern Recognition (CVPR 2001), Kauai, Hawaii, pp. 423–430 .

[14] Shiqi Yu ,Tieniu Tan (2009)."A Study on Gait-Based Gender Classification," *IEEE Transactions on Image Processing*, vol. 18, NO. 8.

[15] C.D., Cutting, J.E., Kozlowski, L.T. Barclay, (1978).”*Temporal and spatial actors in gait perception that influence gender recognitio”.* Perception & Psychophysics 23(2), pp.145–152.

[16] N.F. Troje, (2002).”*Decomposing biological motion: A framework for analysis and synthesis of human gait patterns”.* Journal of Vision 2(5), pp.371–387.

[17] J.W., Gao, H. Davis, (2004).”*Gender recognition from walking movements using adaptive three-mode pca”.* In: IEEE CVPR Workshop on Articu-lated and Nonrigid Motion IEEE Computer Society Press, Los Alamitos

[18] L. T. Kozlowski and J. E. Cutting, (1977). *“Recognizing the sex of a walker from a dynamic point-light display”*. Percpt. Psychophys., vol. 21, pp. 575–580.

[19] L. and Grimson, W. Lee, (2002). "Gait analysis for recognition and classification.," in *in Proc. 5th IEEE Int. Conf. Automatic Face and Gesture Recognition*, Washington, pp. 155–162.

[20] G. Mather and L. Murdoch, (1994). *“Gender discrimination in biological motion displays based on dynamic cues,”*. in Proc. Biological Sciences B, pp. 273–279.

[21] S., Tan, T., Huang, K., Jia, K., and Wu, X. Yu, (2009).”*A study on gait-based gender classification”*.IEEE Transactions on Image Processing., 18(8) pp.1905–1910.

[22] M. Nazir, N. Naveed and N. Riaz. S. A. Khan, (2011) .*“Efficient Gender Classification Methodology using DWT and PCA”.*pp. 155-158.

[23] Siti Zura A. Jalil, "Frequency Radiation Characteristic Around The Human Body," in *Universiti Teknologi Malaysia International Campus* , Kuala Lumpur, Malaysia , pp. 1473-8031.

[24] Michelle Karg. (2010).”*Recognition of Affect Based on Gait Patterns*.”: IEEE Transactions on Systems”, germany .

[25] S. Sarkar, (2011)."USF Human ID Gait Baseline ," *Database Release Agreement. USF Human ID.*

[26] M.S.Nixon,M.G.Grant and J.N.Carter J.D. Shutler, (2002)."On a large sequnce-based human gait database," in *In Proc.of 4th Intrnational Conferences in Soft Computing*, Nottingham,UK, , pp. 66-71.

[27] *CASIA Gait Database*. (2005).: http://www.cbsr.ia.ac.cn/ english/index.asp",

[28] M. Piccardi, (2004). "Background subtraction techniques: a Review," *: IEEE International Conference on Systems*, vol. 4, pp. 3099–3104.

[29] David A.Winter. (1990)., *Biomechanics and Motor Control of Human Movement, Second Edition.* , New York,: Published by John Wiley & Sons.

[30] Vipin Saini , Y.K Jain, Surender Dhiman. Ashutosh Kharb, (13, July 2011). "A Reviw Of Gait Cycle and ITS Parameters " *IJCEM International Journal of Computational Engineering & Management.*

[31] Gaurav, and Pradeep Kumar Bhatia. Kumar. (2014)."A Detailed Review of Feature Extraction in Image Processing Systems" *IEEE Fourth International Conference on Advanced Computing & Communication Technologies (ACCT).*

[32] Jasvinder Pal Singh. Arun Kumar Jhapate. (2011)."Gait Based Human Recognition System using Single Triangle," *International Journal of Computer Sci ence and Technology*, pp. 128-131.

[33] Shweta Ezra. Pratibha Mishra, (2011). "Human Gait Recognition Using Bezier Curves.," *International Journal on Computer Science and Engineering (IJCSE), ,* pp. 969-975.

[34] J. Han and B. Bhanu., (2006)."Individual recognition using gait energy image," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, pp. 28(2):316–322.

[35] Mary She, Saeid Nahavandi, Abbas Kouzani Jin Wang, (2010)."A Review of Vision-based Gait Recognition Methods for Human Identification" , *IEEE Computer Society, 2010 International Con-ference on Digital Image Computing: Techniques and Applications,* pp. 320 – 327.

[36] K. Bashir ,S. Gong. and T. Xiang.(2008). "Feature selection for gait recognition without subject cooperation". *In BMVC* , vol.27.

[37] C. E. SHANNON, (1948). "A Mathematical Theory of Communication," *Reprinted with corrections from The Bell System Technical Journal, ,* vol. 27, pp. 379–423, 623–656.

[38] S. Mallat, (1998). "*A wavelet Tour of Signal Processing*", San Diego: Academic Press.

[39] C.Nastar and N.Ayach, (1996)."Frequency-based nonrigid motion analysis," *IEE Trans.Pattern Anal.Mach.Intell*, vol. 18, pp. 1067-1079.

[40] A. Amira & P. Farrell, (2005). "An Automatic Face Recognition System Based on Wavelet Transforms" IEEE Institute of Electronics, Communications and Information Technology (ECIT)

[41] Feray Özsakabaşi, "Classification of forest areas by k nearest neighbor method" .in *middle east technical university*, ANTALYA, 2010.

[42] Kanak Saxena J. S. Raikwal, "Performance Evaluation of SVM and K-Nearest Neighbor Algorithm over Medical Data set," *International Journal of Computer Applications (0975 – 8887)*, vol. 50, 14 ,July 2012.

[43] V. N. Vapnik. (2000).*The Nature of Statistical Learning Theory."* Springer, Newyork: 2nd edition.

[44] M., Jain, N., Hanmandlu, M. & Chetty, G.Jeevan, "Gait recognition based on gait pal and pal entropy image.," in *s.l., s.n.*, 2013., pp. 4195-4199..

[45] Plataniotis, K.N., Hatzinakos, D. Boulgouris, N.V., (2004)."An Angular Transform of Gait Sequences for Gait," *In: Proc. IEEE Int. Conf.Image Processing.* , Singapore, pp. 857–860.

[46] J. Lu, and Y. P. Tan, (2010). "Uncorrelated discriminant simplex analysis for view-invariant gait signal computing," Pattern Recognition Letters, vol. 31, pp. 382–393,

Appendix A

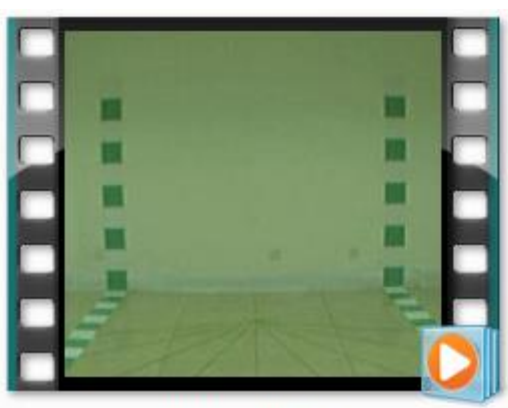
One person has contain 6 sequences

012-nm-01-090

012-nm-02-090

012-nm-03-090

012-nm-04-090



012-nm-05-090

012-nm-06-090

Appendix B

Decision level fusion for each classification K=1

STD	AGEnEI	VGEnEI	AVGEnEI	Fusion
Nu	0.970444	0.963222	0.961556	0.997667
CB	0.87414	0.903978	0.914364	0.921676
CW	0.870314	0.83586	0.823584	0.862975

K=3

STD	AGEnEI	VGEnEI	AVGEnEI	Fusion
Nu	0.963556	0.953778	0.953333	0.995222
CB	0.88819	0.885224	0.897401	0.899014
CW	0.870197	0.840296	0.817097	0.863728

K=5

STD	AGEnEI	VGEnEI	AVGEnEI	Fusion
Nu	0.953111	0.939	0.939333	0.991111
CB	0.887984	0.873513	0.891452	0.892115
CW	0.877769	0.825645	0.826326	0.860851

SVM

STD	AGEnEI	VGEnEI	AVGEnEI	Fusion
Nu	0.972889	0.967444	0.944111	0.996556
CB	0.666711	0.662903	0.788987	0.694185
CW	0.762007	0.81198	0.829919	0.818817

Appendix B-1

Sample Gait Features and Their Fusion Levels

Cycle 1 (R=1) for k=1

PIN*	AGEnEI	VGEnEI	AVGEnEI	Fusion Levels
1	0	0	1	0
2	0	1	1	1
3	1	0	0	0
4	0	1	0	0
5	0	1	1	1
6	1	1	0	1
7	1	1	0	1
8	1	0	0	0
9	1	0	1	1
10	1	0	1	1
11	0	0	0	0
12	1	0	0	0
13	1	1	0	1
14	1	1	1	1
15	0	1	1	1
16	0	1	1	1
17	0	1	1	1

(Average of
Fusion Levels FL1= 91%)

Cycle 2 (R=2) for k=1

PIN*	AGEnEI	VGEnEI	AVGEnEI	Fusion Levels
1	0	0	1	0
2	0	1	1	1
3	1	0	0	0
4	0	1	0	0
5	0	1	1	1
6	1	1	0	1
7	1	1	0	1
8	1	0	0	0
9	1	0	1	1
10	1	0	1	1
11	0	0	0	0
12	1	0	0	0
13	1	1	0	1
14	1	1	1	1
15	0	1	1	1
16	0	1	1	1
17	0	1	1	1

(Average of
Fusion Levels: FL2=94%)

.
.
.

Cycle 3 (R=3) for k=1

PIN	AGEnEI	VGEnEI	AVGEnEI	Fusion Levels
1	0	0	1	0
2	0	1	1	1
3	1	0	0	0
4	0	1	0	0
5	0	1	1	1
6	1	1	0	1
7	1	1	0	1
8	1	0	0	0
9	1	0	1	1
10	1	0	1	1
11	0	0	0	0
12	1	0	0	0
13	1	1	0	1
14	1	1	1	1
15	0	1	1	1
16	0	1	1	1
17	0	1	1	1

[Average of Final Fusion Level=$\frac{FL1+FL2+\cdots+FL30}{30}$] (Final Average of Fusion Levels 97%)

*PIN Person Identification number