Investigation of Gait Representations and Partial Body Gait Recognition

Submitted for the degree of Doctor of Philosophy

Department of Computer Science
School of Mathematical, Physical and Computational Sciences

Chirawat Wattanapanich

September 2018

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

……………………………

Chirawat Wattanapanich

Abstract

Recognising an individual by the way they walk is one of the most popular research subjects within the field of soft biometrics in last few decades. The advancement of technology and equipment such as Close Circuit Television (CCTV), wireless internet and wearable sensors makes it easier to obtain gait data than ever before. The gait biometric can be used widely and in different areas such as biomedical, forensic and surveillance. However, gait recognition still has many challenges and fundamental issues. All of these problems only serve as a researcher's motivation to learn more about various gait topics to overcome the challenges and improve the field of gait recognition.

Gait recognition currently has high performance when carried out under very specific conditions such as normal walking, obstruction from certain types of clothing and fixed camera view angles. When the aforementioned conditions are changed, the classification rate dramatically drops. This study aims to solve the problems of clothing, carrying objects and camera view angles within the indoor environment and video-based data collection. Two gait related databases used for testing in this study are CASIA dataset B and OU-ISIR Large population dataset with Bag (OU-LP-Bag). Three main tasks will be tested with CASIA dataset B while only gait recognition is tested with OU-LP-Bag.

The gait recognition framework is developed to solve the three main tasks including gait recognition by identical view, view classification and cross view recognition. This framework uses gait images sequence as input to generate a gait compact image. Next, gait features are extracted with the optimal feature map by Principal Component Analysis (PCA) and then a linear Support Vector Machine (SVM) is used as the one-against-all multiclass classifier.

Four gait compact images including Gait Energy Image (GEI), Gait Entropy Image (GEnI), Gait Gaussian Image (GGI) and the novel gait images called Gait Gaussian Entropy Image (GGEnI) are used as basic gait representations. Then three secondary gait representations are generated from these basic representations. These include Gradient Histogram Gait Image (GHGI) and two novel gait

representations called Convolutional Gait Image (CGI) and Convolutional Gradient Histogram Gait Image (CGHGI). All representations are tested with three main tasks.

When people walk, each body part does not have the same locomotion information, for example, there is much more motion in the leg than shoulder motion when walking. Moreover, clothing and carrying objects do not have the same level of affect to every part of the body, for example, a handbag does not generally affect leg motion. This study divides the human body into fourteen different body parts based on height. Body parts and gait representations are combined to solve the three main tasks.

Three combined parts techniques which use two different parts to solve the problem are created. The fist is Part Scores Fusion (PSF) which uses the summation score of two models based on each part. The highest summation score model is chosen as the result. The second is Part Image Fusion (PIF) which concatenates two parts into a single image with a 1:1 ratio. The highest scoring model which is generated from image fusion is selected as the result. The third is Multi Region Duplication (MRD) which uses the same idea as PIF, however, the second part's ratio is increased to 1:2, 1:3 and 1:4. These techniques are tested on the gait recognition by identical view.

In conclusion, the general framework is effectively for three main tasks. GHGI-GEI which is generated from full silhouette is the most effective representation for gait recognition by identical view and cross view recognition. GHGI-GGI with lower knee region is the most effective representation for view angle classification. The GHGI-GEI CPI combination between full body and limb parts is the most effective combination on OU-LP-Bag. A more detailed description of each aspect is in the following Chapters.

Table of Contents

List of Figure

List of tables

Acknowledgements

I would like to thank the following people who have supported and helped me throughout my long way of PhD.

Firstly, my supervisors Associate Professor Hong Wei and Professor James Ferryman for their patience, motivation and immense knowledge. Their guidance helped me in all the time of research and writing of this thesis.

The royal Thai government for give me opportunity to do PhD.

I would like to thank Thailand PhD students @ Reading University group and Thai corner staffs for their support and help.

Finally, I would like to thank my family; my father, mother, 2 brothers and sister for their support and help.

Chapter 1 Introduction

1.1 Motivation

Biometrics is the technology used to recognize human individuals based on their physical appearance and behavioural attributes such as face, fingerprint, iris, blood vein, keystroke pattern, written signature, voice and gait. In the case of a classical biometric system, it starts with the enrolment process which acquires personal biometric data from sensors or cameras. Then the personal features are extracted and stored in a biometric template or database. When a person accesses a biometric system, the system acquires the personal biometric information or features by using sensor(s). Then the system makes the decision based on a matching result between the extracted feature and the biometric template as it can be seen in Figure 1.1.

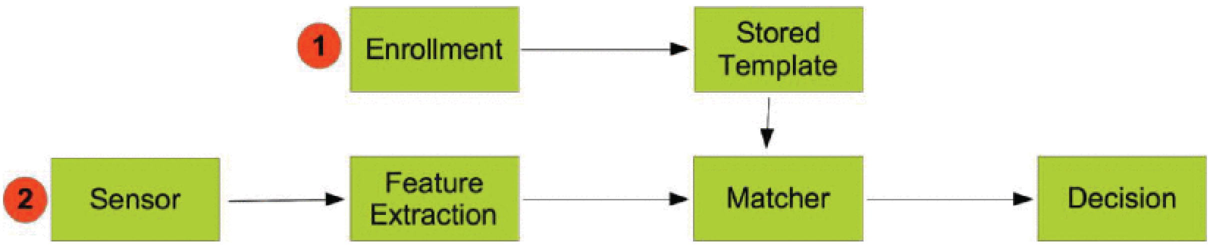


Figure 1-1: Classical Biometric System [1]

Biometric data can be used to recognize other types of attributes, such as age, gender, weight, height, ethnicity and body mass index. Nonetheless, common biometric systems usually use biometric data to recognize human individuals, as an identifier. Currently, biometric applications are prevalent in daily life because of technology advancement, for example, mobile device login or postal signature checking.

Biometric data is easier nowadays to capture than the past because of the popularity of relevant equipment. Due to these advancements, biometrics has become a highly active area of research. Gait recognition is just one branch of biometrics that has benefited from such technological advancements and increased study within the last decade. The upside to gait recognition technology is that generated biometric data can be captured from distance, gait features can be extracted from videos recorded by closed circuit television (CCTV) cameras which may have low resolutions, therefore making the other biometrics such as facial recognition difficult or even impossible. Furthermore, gait characteristics are difficult to conceal.

Gait biometrics can be captured by various sensors and a video camera. Sensor based devices need specific equipment such as accelerometers and gyroscopes. Sensor devices are also normally fixed upon the target subject. Thus, they generate more precise data which contributes to better recognition rates when compared with video based data. Conversely, a video-based gait data capturing device is easier to setup and it does not need special equipment. With the intention of capturing more gait information, some research uses specific cameras such as deep cameras [2] and the Microsoft Kinect camera [3]. In conclusion, video based gait recognition is more suitable and versatile for real world applications.

In gait recognition research the most common challenges are appearance changes caused by carrying objects, body parts being obscured by certain clothing and camera angles. There are also many other factors that can affect the gait recognition rate, such as walking speed, walking surface, seasonal footwear, as well as the aforementioned issues regarding clothing, carried objects and camera angles. Carrying an object may change a person's appearance more than changing their gait itself. This appearance change can have an undesirable effect on the recognition rate. Clothing change also has a negative effect on gait recognition. This is especially an issue with trench coats or thick jackets. Both changes, i.e. carrying object and clothing, have been solved partially in published research, nevertheless there is still room for improvement with regards to these recognition rates when compared with the rates for normal walking recognition. While the camera's view angle directly affects the gait characteristics. For example, a lateral view can capture the most gait movement, while a frontal view captures less movement especially the joint movements at the hip, knee, and ankle. The different characteristics in each view angle make it difficult to recognize a person from cross views. Even gait recognitions that are performed from an identical view angle have low recognition rates when the same person carries an object or wears a coat.

All of the reasons/challenges previously mentioned motivated this study to focus on video based gait recognition systems which can solve the problems caused by carrying objects, clothing and view angles.

1.2 Aims of the work

The aim of this study is to create a robust and reliable gait recognition system with the ability to identify a person using various different camera angles and appearance changes using the compact gait image representation, gait feature extraction by Principal Component Analysis (PCA), and classifier as Support Vector Machines (SVMs).

1.3 Objectives

The objectives of this work are specified as below.

- To develop a general gait framework that can solve both view angle and appearance change problems
- To investigate suitable gait representations that are reliable with appearance changes caused by the subject carrying a bag and wearing a coat
- To investigate how effective partial body analysis can be used for gait recognition to alleviate some of the issues caused by appearance changes, to verify efficient body parts and their combinations to tackle appearance changes based on anthropometric measurement

1.4 Contributions

The contributions to the knowledge of this study are listed below.

- It develops a general framework for gait recognition, view angle classification, and cross view gait recognition. This framework uses gait compact image as input, contains gait feature extraction with optimal feature map by PCA and recognition with SVMs. The different structures of this framework can cope with various tasks through the optimal feature map. View angle classification uses samples from all view angles to generate the optimal feature map. Both gait recognition by identical view and cross view recognition use specific view angle samples to generate the optimal feature maps. Gait features extracted for gait recognition by identical view uses the optimal feature map having the same view angle as a probe sample, while gait feature extracted for cross view uses the optimal feature map having the same view angle with gallery samples.

- New gait representations are developed. These include (1) Gait Gaussian Entropy Image (GGEnI) which is generated by Gaussian and entropy technique, (2) Convolutional Gait Image (CGI) which are generated by single convolutional and normalize technique, and (3) Convolutional Gradient Histogram Gait Image (CGHGI) which is generated by both convolutional and HOG techniques. CGI and CGHGI are not directly generated from gait image sequences but they are generated from basic gait compact image. Four compact images include Gait Energy Image (GEI), Gait Entropy Image (GEnI), Gait Gaussian Image (GGI) and GGEnI are used as input image. In gait recognition by identical view, GEnI has the best recognition rate compared with other basic gait compact images. The convolutional technique can slightly improve the classification rate of all basic gait compact images. It is a HOG technique which dramatically improves the recognition rate of basic compact gait image.
- Gait recognition with partial body base on anthropometric measurement which is divided into fourteen different parts based on body height is used for gait recognition. Six parts which have highest recognition rates are full body, head to chest, limb, lower hip, lower knee and ankle. Head is another part which has a high recognition rate in CASIA dataset B testing, but it has a low recognition rate in OU-ISIR Large population with Bag. Body parts have low recognition rate, while the upper chest and lower body have relatively high recognition rate. Lower knee has the best recognition rate in gait recognition by identical view when compact gait images

are GEI and CGI, while full body has the best classification rate in gait recognition by identical view when gait representations are GHGI and CGHGI.

- Gait recognition with body part combinations, such as Part Score Fusion (PSF), Part Image Fusion (PIF) and Multi Region Duplicate (MRD) recognizes a person by two selected parts. PSF creates two models from two selected parts then the recognition results are chosen from the highest total score from the two models. PIF concatenates two parts into one gait image then the gait model is created from the combined image. MRD use the same idea with CPI, however, the ratio between the two parts are not one to one. All combinations of body parts can improve the recognition rate when full body silhouette cannot be taken into account. However, for CASIA dataset B, the best recognition rate is from GHGI full body without any combinations, whilst CPI-GHGI which combined full body and limb has the best recognition rate in OU-ISIR Large population dataset with Bag. This means that if a full body is available, it may provide the best solution for gait recognition. In the case when a full body is not available, for example, if some body parts are occluded, the recommended body parts or their combinations can be used for gait recognition.
- View angle classification identifies the view angle of probe or testing sample. Gait compact image is used as the input of this system, then the gait features are calculated by the optimal view feature map. This map is generated from the components of eleven view angle samples by PCA. In CASIA dataset B, eleven view models are created from gait features by SVM. GGEnI has the best view classification rate compared with GEI, GEnI and GGI. GGHGI-GGI has the best classification rate compared with other gait representations in this study. A full body still has the best classification rate when compared with recognition rates by using other body parts, followed by part 11 (lower knee).
- Cross view recognition and framework which are tested on CASIA dataset B use single view gallery models to identify probe samples from all view angles. This experiment uses GEI and GHGI-GEI as input. The result shows that GHGI greatly improves the recognition rate

compared with GEI. GHGI-Full body has the best recognition rate followed by part 7 (chin to finger) which covers the main upper body part. The most variable region which took effect from carrying a bag and wearing a coat is the body part which covers from neck to hip. When the part of this region is used to recognize individuals, the recognition rate is normally lower than the other body parts. Although HOG technique improves the recognition rate, the recognition rate is still lower than those taken from lower body parts in gait recognition with an identical view angle. However, body parts seem more robust in cross view gait recognition because its silhouette does not change much when the camera view angle is changed.

1.5 Thesis Overview

This thesis is structured as follows:

Chapter 2 provides a review of existing gait recognition systems and techniques. It includes gait recognition system overview, gait representation from video, partial body gait recognition, classifiers, gait databases and a summary of gait recognition performance especially the related research on CASIA dataset B and OU-ISIR Large population dataset with Bag.

Chapter 3 describes the general gait recognition system and basic gait representations in this study. Four gait representations, GEI, GEnI, GGI and GGEnI are introduced with CASIA dataset B. The first experiment is the Nearest Neighbour (NN) and SVM comparison which also includes PCA for feature extraction. The second experiment is the impact of different view angles to gait recognition. The third experiment is for a different number of training samples which uses only the normal walk dataset to train a model. The fourth experiment involves training samples from various appearances.

Chapter 4 introduces the three secondary gait representations including CGI, GHGI and CGHGI which are generated from the basic gait compact image as described in Chapter 3. All experiments use CASIA dataset B. Three main experiments are conducted based on each gait representation. The first experiment is for CGI which is generated by three different calculation blocks including convolutional, normalization and average. Deep learning is also introduced as a part of this experiment. The second experiment is for GHGI which also includes an introduction to HOG parameters. The third experiment is the CGHGI which combines both convolutional and HOG techniques in three different ways.

Chapter 5 presents the gait recognition with the partial body. All experiments use CASIA dataset B. Fourteen different parts based on silhouette height are investigated in five main experiments. The first experiment is for the single body part gait recognition by identical view. The second to forth experiments are for the combined body part gait recognition by identical view which is divided into three different combinations including Part Scored Fusion (PSF), Part Image Fusion (PIF) and Multi Region Duplication (MRD). The fifth experiment is for the view classification and cross view recognition.

Chapter 6 repeats the experiments in Chapters 3 to 5 with the OU-ISIR Large population dataset with Bag. This dataset focuses on the appearance change of carrying a bag. This Chapter uses four kinds of gait representations including GEI, CGI, GHGI and CGHGI. Two main experiments are conducted. The first experiment is the single part gait recognition with fourteen parts. The second experiment is the combined part gait recognition which is divided into three kinds, CPS, CPI and MRD.

Chapter 7 concludes the overall findings of the research and provides the direction for future work.

1.6 List of publications

The following papers have been published:

- Wattanapanich C. and Wei H. (2016). **Investigation of Gait Representations in Lower Knee Gait Recognition**. In *Proceedings of the 5th International Conference on Pattern Recognition Applications and Methods - Volume 1: ICPRAM,* ISBN 978-989-758-173-1, pages 678-683. DOI: 10.5220/0005817006780683
- Wattanapanich C. and Wei H. (2017). **Investigation of New Gait Representations for Improving Gait Recognition.** International Journal of Computer, Electrical, Automation, Control and Information Engineering-volume 11, eISSN: 1307-6892, pages 1272 - 1277

Chapter 2 Literature Review

Gait recognition and analysis has a long history. The first human gait observation was “On the Gait of Animal” written in 350 BC by Aristotle. This work was improved to “On the Movement of Animals” which studied the physiology and limb movement by Borelli in 1679 [4]. In 1836, the Webber brothers made a contribution with their work, “Mechanics of the Human Walking Apparatus”[5]. In 1889, Braune and Fisher published their work on “The Human Gait”[6]. At first, gait analysis was used for medical fields such as cerebral palsy, Parkinson’s disease and neuromuscular disorder. Individual gait discrimination was studied in the 1960s. Murray et al used the photographic method to analyze the normal gait pattern in 1964 [7]. The first gait biometric with video-based analysis was “Analyzing gait with spatiotemporal surface” by Niyogi and Adelson[8]. When digital video become a popular technology, DAPRA lunched the distance research program called HumanID in the early 2000s. HumanID gait challenge dataset was the big impact of this project [9, 10]. At the same time period, CMU MoBo[11] and Southampton[12] gait database were published. All gait database boosted the video-based gait recognition research. The advantage of equipment technology and a number of following standard gait datasets made the gait recognition research be a popular and active biometric in the last few decades.

In this Chapter, the gait recognition and related systems are reviewed. Another important part of this Chapter are the different algorithms of Gait representations and Gait classifications which are reviewed in detail. The last section describes the other supporting techniques.

2.1 Gait Recognition System Overview

Normally, a gait recognition system has two phases: training and testing. However, the detail of each phase may vary between different systems. An overview of gait recognition systems from video is shown in Figure 2.1. The first step is background subtraction which separates a target object from a background of each image frame in the input video sequence. The second step is feature extraction which computes each person's representing data. The final step in the training phase is classifier training which creates a model for each person from gallery or training samples. The final step in the recognition phase is classifier prediction which votes similar score for each personal model in the database. The highest similarity model normally is chosen as a result of this step.

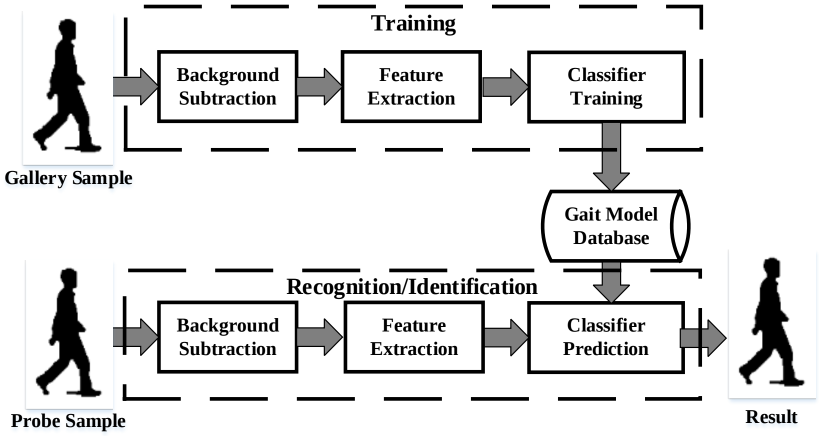


Figure 2-1: Gait Recognition System Overview

All three steps are important and there are various techniques and methods in each step. If a standard gait database is chosen as research input, the first step may be skipped. Many standard gait databases already provide ground truth sequence images or gait representation images. These provided data can be directly processed by a feature extractor in the second step. Then gait features are used to train a personal gait model by a classifier in the third step. Although gait recognition depends on the associated feature, feature reduction methods and classifiers, effective features are critical for gait recognition [13]. This study focuses on the second step i.e. feature extraction which is explored in more detail in the following sections.

2.2 Gait Representation

Gait recognition originally began with video-based analysis. It has been extended to many other ways. Apart from a video sequence, there are various input sources for gait recognition systems such as an accelerometer or gyroscope from a smartphone [14-16], smart watch[17] or wearable sensor[18]. The collected data is used to represent gait characteristics which may uniquely represent a person. Gait representation is created based on the criteria and basic equipment of a gait recognition system. The sensor-based system which mainly captures the locomotion information from sensors is normally tended to develop human skeletons for gait recognition [3, 19-21]. There are many sensor types in this system such as pressure sensor[22], depth sensor[23-25] or inertial sensor[14-17]. This type of system may capture accurate details of the targeted person, however, they need specific system settings which are suitable for the private or specific area such as IT Company, specialize factory or health care. A video-based system is flexible in the real world, especially a single camera-based system which can be applied to closed circuit television (CCTV) in a public area without any special setting.

The gait representation varies in different studies. However, the recognition results depend on the association between the extracted feature, feature or data reduction methods and classification methods. Most gait recognition usually decides their performance by the match score between two gait samples. This score can be extended to a score metric called recognition rate. In identification mode, the performance metrics are commonly called identification rate or classification rate (CR) or correct classification rate (CCR). It reports the correct identification between probe sample and the labelled gallery. In verification mode, the matching score is compared with the threshold which is the divider point between “match” and “not matches” result. The performance indicator in verification mode are the false acceptance rate (FAR), false reject rate (FRR), detection error tradeoff (DET), receiver operating characteristic (ROC) and equal error rate (ERR) [13]. All examples in this section are reviewed with their related information.

2.2.1 Gait representation from video

There are typically two approaches which have usually been used to represent gait features in camera-based systems. The first approach is model-based which creates a model/skeleton of each person in a video sequence. Then gait features are extracted from these models. The other approach is model-free which operates directly on the gait image sequence.

2.2.1.1 Model-based approach

The model-based approach retrieves static and dynamic human body parameters from modelling which involves image feature mapping into a physical model component of the human body over a complete gait cycle as shown in Figure 2.2. One complete gait cycle is the period from the first double support stage, which has the longest distance between left and right foot, until the third double support stage. The common 2D models are in the format of the stick and volumetric model. The movement of the hip, knee and ankle are usually extracted from the video. The angular movement between each joint is used to identify individuals.

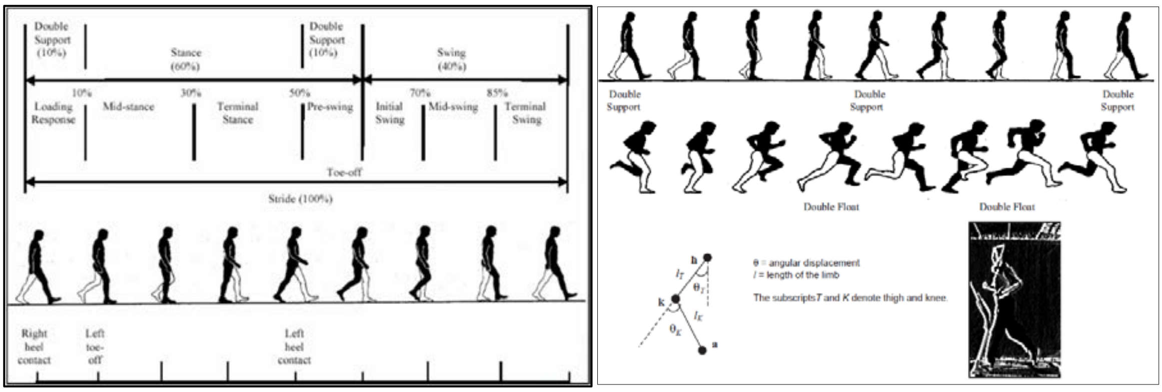


Figure 2-2: Model of the thigh and lower leg for walking and running [26]

An example of model-based research follows. BenAbdelkader et al identified a person by stride and height parameters based on 45 subjects. The classification rate with stride was 21% while the recognition rate by stride and height parameters was 49% [27, 28]. Yam et al use the model of the thigh and lower leg motion in walking and running gait recognition as shown in Figure 2.2. A testing dataset was captured from 20 subjects which had five samples of walking and running per person. The classification rate for running by thigh and knee was 90% with k-nearest neighbor[26]. Ng et al proposed a multi-view model-based with joint detection approach which focused on hip, knee and ankle joint position as shown in Figure 2.3. MMUGait database, 82 subjects walking in normal condition and 19 subjects walking in covariate factors, was introduced in this research. The classification rate with Support Vector Machine (SVM) with radial basis function (RBF) was 96.0%, 93.6% and 94.2% for side-view, oblique-view and both view combination, respectively [29]. Depth camera becomes affordable, such as Microsoft Kinect which provides skeletal tracking that can track the skeleton image of a person moving on the field of view. However, the Kinect 1.0 sensor works only in the range of one to three meters. Kinect 2.0 can capture and track 25 joints but it still has a working range limitation of four meters and its extended range is up to six meters. Dikovski et al use a Kinect 1.0 sensor which gives 20 joints information through Kinect skeleton images as it can be seen in Figure 2.4. Testing dataset captured from 15 subjects. The lower body limbs features that applied with Principal Component Analysis (PCA) has the classification rates of 79.59% when the classifier was SVM RBF using sequential minimal optimization (SMO) [19]. Kang et al use the frontal-view feature from Kinect 2.0 as it can be seen in Figure 2.5. Testing dataset captured 30 subjects with 5 sequences per subject in frontal-view. The correct classification rate was 90.39% using RBF network when the features were the combination of joint angle, relative distance and anthropometric feature [30]. Multi-sensor may be set up in some scenarios. Zou et al use three inputs from a smartphone and RGB-D (colour and depth) camera as show in Figure 2.6. Gait features were EigenGait and TrajGait which are calculated from acceleration data and colour and depth images, respectively. Testing dataset captured 50 subjects with 48 samples per subject under different speed and eight covariate conditions. When gait features were collected with 4 walking steps, the classification rates by linear SVM were 96.59%, 93.98% and 91.98% for normal, fast and both speed, respectively [23].

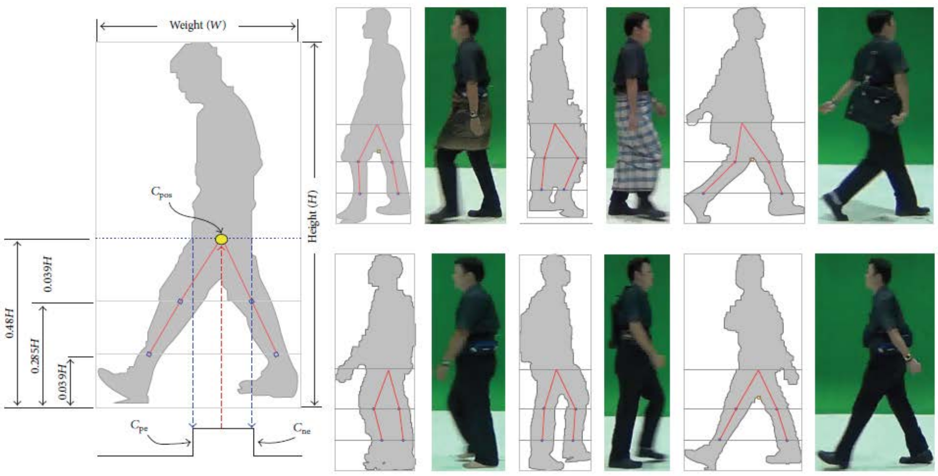


Figure 2-3: Model of the thigh and lower leg for walking and running [29]

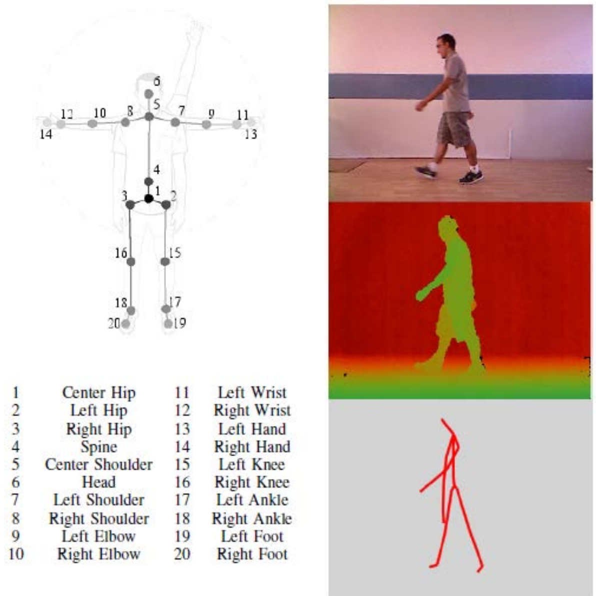


Figure 2-4: Available joints and skeleton image from the Kinect 1.0 sensor [19]

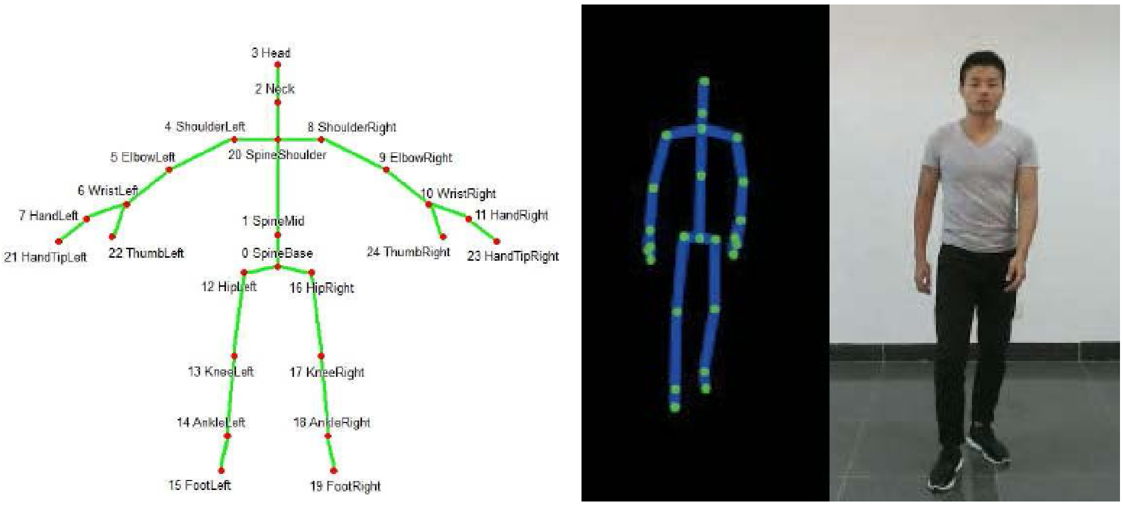


Figure 2-5: Kinect 2.0 sensor and Frontal view data [30]

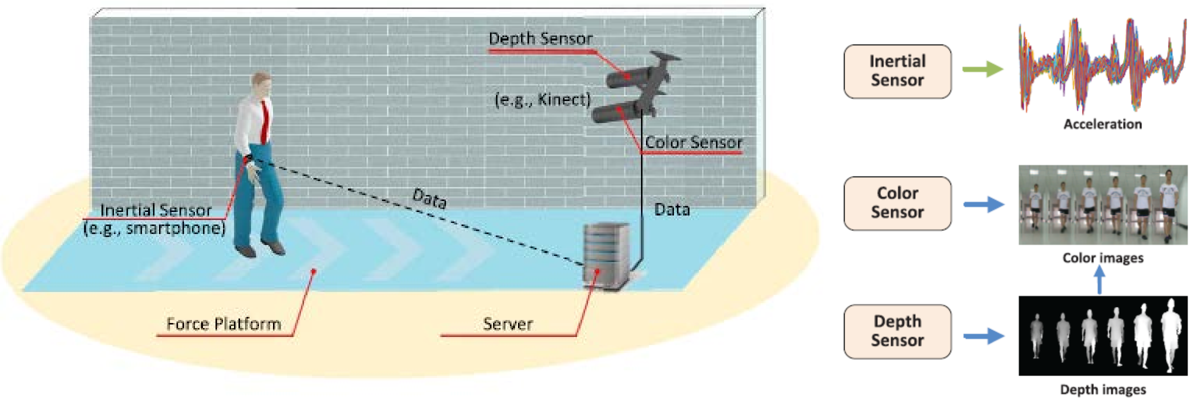


Figure 2-6: Multi-sensor for gait-based person identification [23]

Gait features generated from this approach are more robustness on view, scale, rotation and noise. Gait features have more invariant properties. However, they require high-quality input, specific configuration and devices. They usually capture input from the limited length. They usually have high computational costs. And this approach is not suitable for an outdoor scene. All these reasons motivates the researcher to focus on the model-free approach.

2.2.1.2 Model-free approach

The model-free approach directly derives the gait motion representation from human silhouettes without recognizing the underlying structures such as shape, velocity, and texture. Liu presents the simplest model-free representation called Average Silhouette which calculates over the complete gait cycle. Classification rate using Euclidean distance classifier are 54%, 14%, 25% and 3% for shoe, surface, carry and time covariates for 71 subjects HumanID database[31]. Han and Bhanu propose a spatiotemporal gait representation called Gait Energy Image (GEI) which averages all complete gait cycle image sequence into a single image. Average classification rate under 122 subjects on USF HumanID database is 54.00% using GEI, PCA, Multiple Discriminant Analysis (MDA) and fused Bayesian and Euclidean classifier[32]. This technique is commonly used because it is very simple, fast, and representative to some extent. However, it is sensitive to some conditions, such as object carrying and clothing. Hence there is emerging research that aims to improve the performance of the whole silhouette gait representation. For example, Gait Entropy Image (GEnI) that captures mostly motion information by measuring Shannon entropy for all GEI pixels. Classification rate using component and discriminant analysis (CDA) is 98.3%, 80.1%, 33.5%, 99.1% and 53.5% for CASIA dataset B normal walking, carrying a bag, wearing a coat, SOTON Large dataset and USF HumanID dataset, respectively. GEnI performs better result than GEI, however, it still has low recognition rate in some covariants especially CASIA dataset B wearing a coat, USF HumanID surface and time [33]. Active Energy Image (AEI) is generated from the accumulate of the active region that calculates from the difference of two adjacent silhouette images over complete gait cycle images. Gait feature is extracted by two-dimensional locality preserving projection (2DLPP). Recognition rate is 98.39%, 91.92%, 72.18%, 88.89%, 90.20%, 89.22% and 79.74% for CASIA dataset B normal walking, carrying a bag, wearing a coat, CASIA dataset C normal walking, fast, slow and carrying a bag respectively [34]. Flow Histogram Energy Image (FHEI) is generated from the average Histogram of Optical Flow (HOF) of each silhouette image over the full gait cycle. Real and synthetic FHEI gait template is fused to gait feature which is reduced the data dimension by PCA and LDA. Then part based representation is generated by non-negative matrix factorization (NMF). Average classification rate using NN is 65.07% for USF HumanID database. FHEI also have a problem with surface and time covariat[35], Gait Gaussian Image (GGI) is generated from the average membership value of a pixel over gait cycle that is calculated by the pixel value multiplied by its corresponding Gaussian membership. Classification rate using Euclidean distance are 98.00% and 100% for lateral view CASIA dataset B normal walking and SOTON small database, respectively [36]. Gait Histogram Gaussian Image (GHGI) is generated from the Histogram of Oriented Gradients of GGI. Classification rate using NN are 94.1%, 88.2%, 58.8% and 62.5% for OU-ISIR treadmill A 5km/h, 6km/h, 7km/h and Treadmill B, respectively [37]. An example of the gait representation images is shown in Figure 2.7.

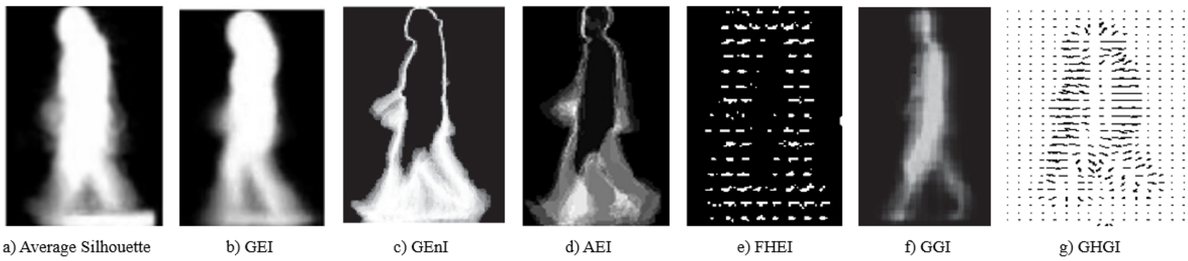


Figure 2-7: Mode-free gait representation examples

The compact gait recognition image is very popular in gait recognition. Nonetheless, there are additional ways of model-free gait representation extraction that directly extract gait feature from silhouette attributes such as contour or centroid. For example, Bo and Wen represent the vector of vertical, horizontal and diagonal of the silhouette outer contour as gait feature template as shown in Figure 2.8. Gait feature uses PCA and LDA to reduce data dimension. Its classification rate using kNN is 87% for a mixed dataset that captured 30 subjects with 4 sequences per subject [38]. Zeng et al recognize an individual by the combination of the height-width ratio of silhouette, the width of the outer contour, the silhouette area and the vertical coordination of centroid as it can be seen in Figure 2.9. Individual gait dynamics are obtained by RBF network via deterministic learning theory. Classification rate is 98.4%, 90.3%, 93.2%, 95.4% and 96.9%for CASIA dataset B normal walking, wearing a coat, carrying a bag, CASIA dataset C normal walking, TUM GAID [39]. Both examples have high classification rate, however, their feature is extracted only in lateral view. The view angle covariate is the problem for both methods.

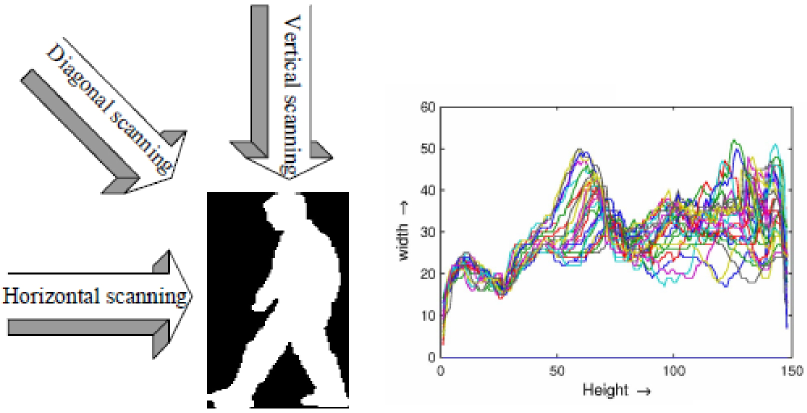


Figure 2-8: Outer contour of complete gait sequences as gait feature [38]

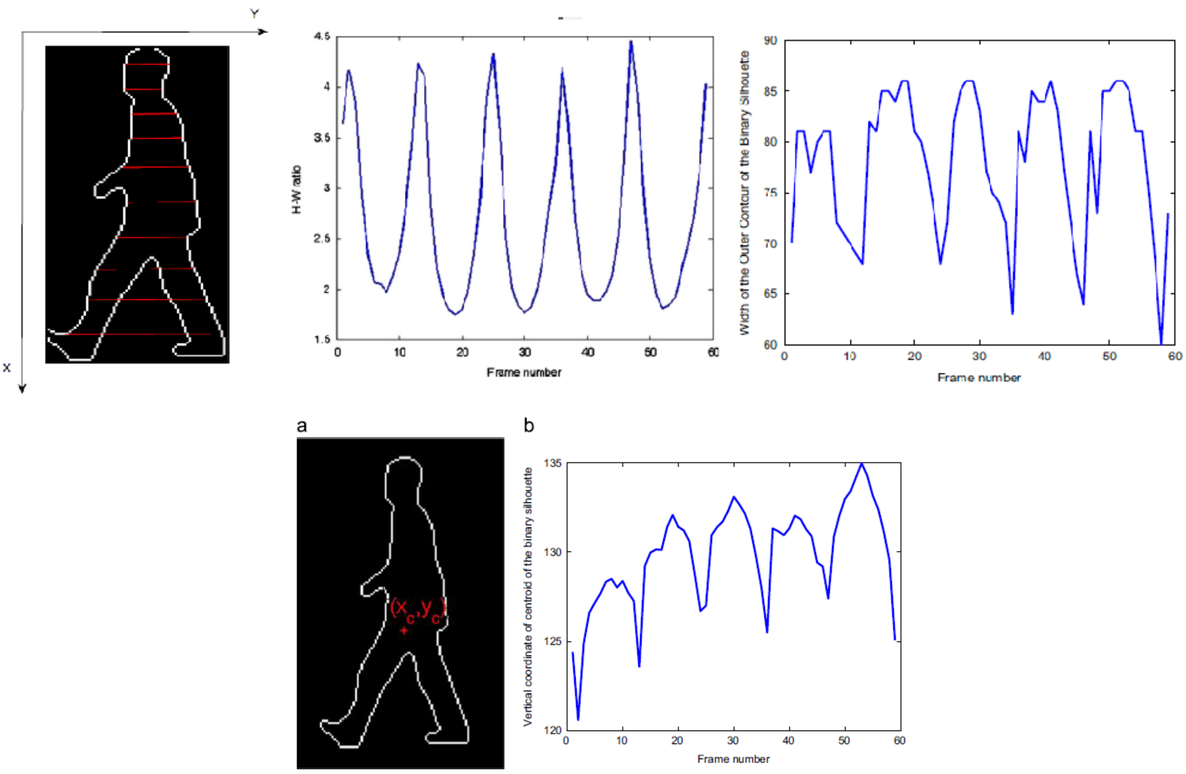


Figure 2-9: Outer contour high-width ratio and centroid coordinate as gait feature [39]

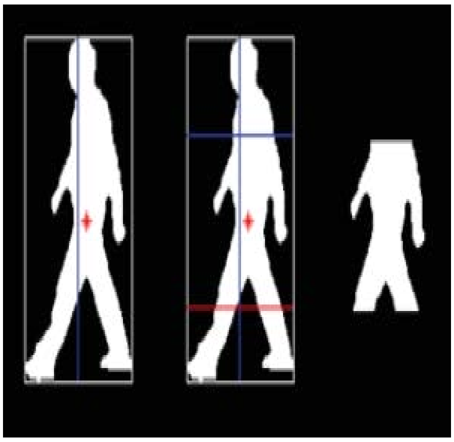
The main advantage of the model-free approach is speed, simplicity, robustness to noise and workability with low-resolution video input. The model free approach is more suitable to use in real world compared with the model-based approach. However, they are sensitive to variant conditions such as walking surface, walking speed, clothes and shoes. Thus many researches prefer this approach and create advanced methods and techniques to solve these problems.

2.2.2 Partial body gait recognition

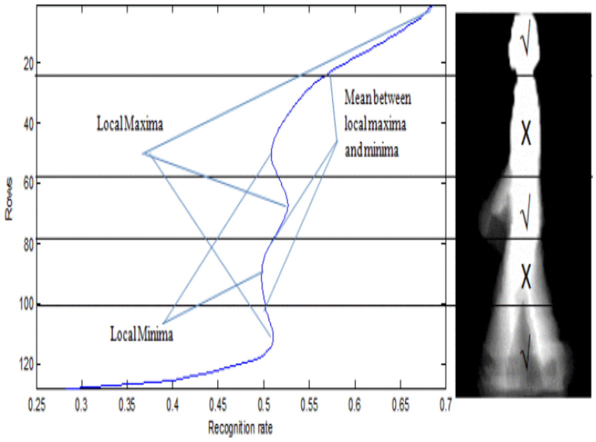
Many research attempts to employ only some body parts to identify the person because some body part is not effective in gait recognition [40-43]. In the model-based approach, the partial body is also popularly used in gait recognition. It needs to find the exact joint position and gait feature is then extracted from each joint. For example, Yeoh et al extract angular trajectory from the hip, knee and ankle joint then gait feature is analyzed by ANOVA. Classification rate is 96.0% on SOTON database using Hill-Climber (HC) with SVM RBF and 76.0% on CASIA dataset B lateral view using HC with ExtraTree (ET) [44].

In the model-free approach, there is no need for the exact estimation for joint positions or human skeleton. Many research uses a reference to divide human silhouette. For example, Shaikh et al use centroid as the reference then select the middle part (1/2 height) as input for gait recognition. The selected part is shown in Figure 2.10a. The classification result by minimum distance classifier based on Euclidean distance shown that partial silhouette has equal or better than full silhouette on CASIA dataset A and CMU-MoBo dataset [45]. Rokanujjaman et al divide GEI into five parts based on the local maxima, local minima and means between local maxima and local minima which calculated from the recognition rate for each row from bottom to top as show in Figure 2.10b. Gait Silhouette Volume (GSV) and Discrete Fourier Transformation are used to generate gait features. Three selected parts are used to recognize individuals with Euclidean distance on OU-ISIR Gait dataset B. The recognition result has better performance than full body [41]. Rida et al use group lasso of motion to select human body part as show in Figure 2.10c. GEI feature is applied with Canonical Discriminant Analysis (CDA).

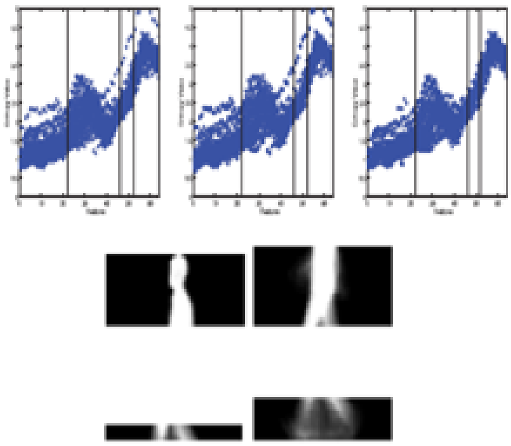
The average CCR of the selected part it better than full body on both lateral view CASIA dataset B and the average CCR under view angle. The main advance point of the selected part is the clothing robustness. The CCR of the selected part under clothing condition is much higher than full body in this study [46]. Yang et al use Convolutional Neural network (CNN) based on Human3.6M and CASIA dataset B to estimate twelve body joints as show in Figure 2.10d. Then Long Short Term Memory (LSTM) is used to generate the gait model. This gait feature model based on twelve joints is used for cross view recognition [47].



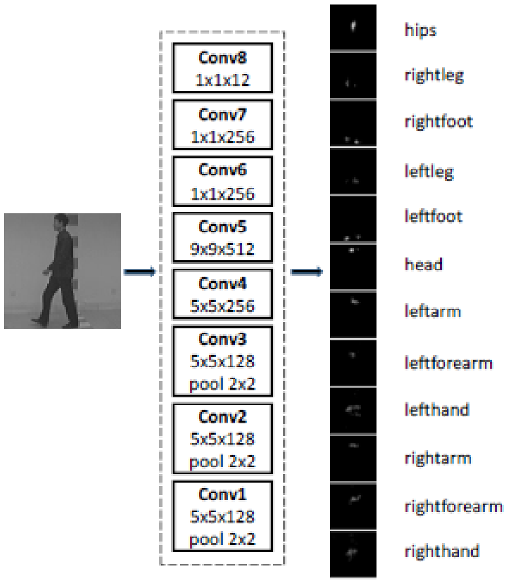
(a) half silhouette from centroid [45]



(b) LocalMaxima and LocalMinima [41]



(c) group lasso of motion[46]



(d) Convolutional Neural Network[47]

Figure 2-10: Example of part segmentation by different techniques

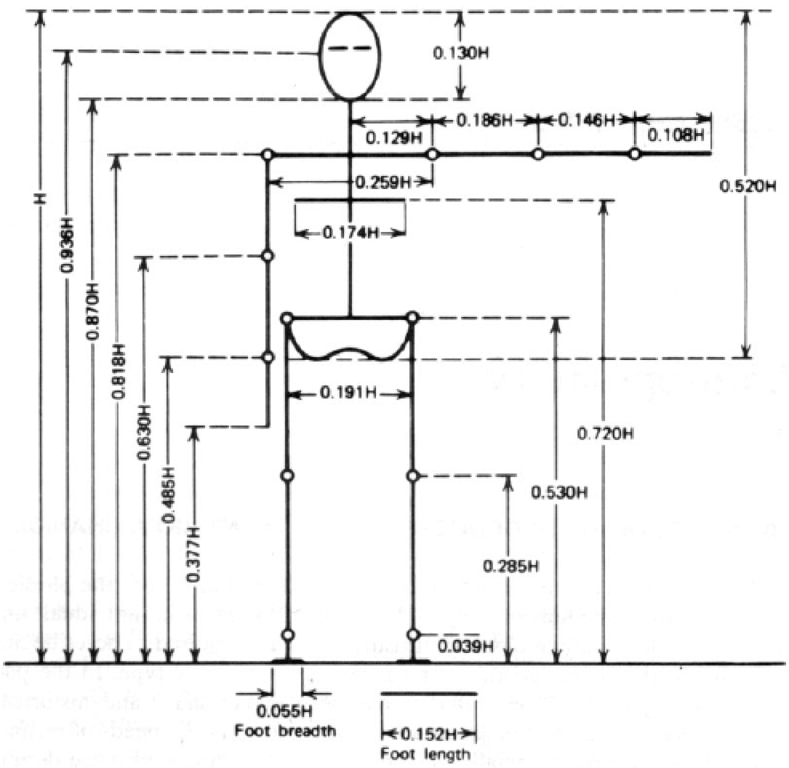
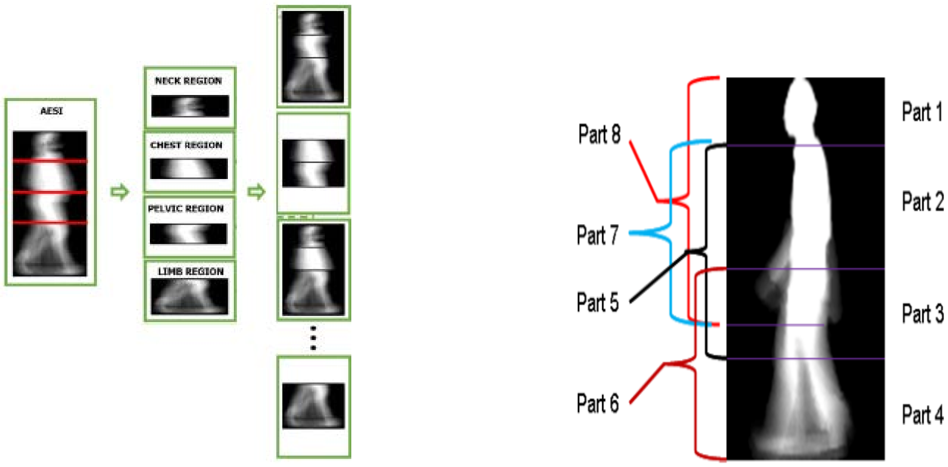


Figure 2-11: Anthropometric measurement [48]

Anthropometric measurement is another reference which is usually used in part segmentation. The precise anthropometric measurement depends on many factors such as nationality, ageing and gender. The example average anthropometric measurement is shown in Figure 2.11 [48]. For example, Nandy et al divide GEI into three different segments include head node, bod torso and leg region. The time series of distance between the boundary and the centroid of each region is used as features. The best recognition rate on OU-ISIR Treadmill dataset D is 84.21% using foot region with cosine distance [49]. Part fusions or part combinations which use more than one segment part to identify a person are also used to increase the recognition rate. For example, Aggarwal and Vishwakarma [50] divide average energy silhouette image (AESI) into four parts including neck, chest, pelvic and limb region based on human anatomy. Final feature is extracted from different part fusions by Zernike moment invariants (ZMIs), the spatial distribution of gradients (SDOGs) and mean of directional pixels (MDPs). Linear kernel SVMs are used as a classifier. The average CCR is 91.47%, 89.7% and 84.67% on CASIA dataset B, OU-ISIR Treadmill B and USF HumanID gait dataset, respectively. Rokanujjaman et al divide gait silhouette into five parts by localMaxima and LocalMinima and eight parts by anatomical properties then all parts are combined together with different trained weights. The results of OU-ISIR Treadmill B shows that GEnI fusion on 5 parts has the best recognition rate of 73.84% while the best recognition rate of full body is 58.87% using GEnI [51].



(a) Four parts divided and fusion[50] (b) Eight parts combination [51]

Figure 2-12: Divided and Fused partial silhouette Example

2.3 Classifier

The main purpose of a gait recognition system is to correctly identify a person by matching an unknown video input against the reference information in the database. Gait feature is the critical part in gait recognition, however, a good recognition results also need a suitable classifier. There are many classifiers that are used in gait recognition such as Nearest Neighbor (NN), k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Hidden Markov Model (HMM), Artificial Neural Network (ANN) and Convolutional Neural Network (CNN).

k-Nearest Neighbor (k-NN) which is the extension of NN is introduced by Cover and Hart[52]. It is a simple, fast and intuitive method which choose the most frequently represented class between the k nearest samples as an answer. It is usually used in practice because it does not need prior knowledge and does not need to retain when the new data is added. However, it has a problem with large-scale data because all data need to calculate distance and store in memory before the decision process. If the training samples are too small, the neighbourhood is small as well. The k-NN decision rule may not effective and it leads to misclassify. The suitable distance function and decision rule can be optimized to produce the best result. Nevertheless, k-NN is still one of the popular classifiers in gait recognition. For example, Arora et al present a gait feature called Gait Information Image (GII) which has two feature types namely energy feature (EF) and Sigmoid feature (SF). The CCR by NN shows that GII-SF has better performance than GII-EF on four gait datasets include CASIA dataset B, SOTON small database, OU-ISIR Treadmill A and Treadmill B, respectively [53]. Mahfouf et al use optical-flow estimation based on the brightness constancy constant. Three kinds of the feature include local, global and histogram-based optical flow feature are used to recognize individual by kNN with Euclidean distance metric and Neural Network based on the autoencoder network. Local flow with angle feature has the best recognition rate of 97.8% using 1-NN on CASIA dataset B [54]. Chaurasia et al develop Random Walk (RW) and Discrete Fourier Spectrum (DFS) method as the gait feature extraction method. The averaged CCRs by 1-NN is 82.0% and 56.1% on CASIA dataset B and USF HumanID gait database [55]. Yang et al use flow histogram energy image (FHEI) which is generated from Histograms of Optical Flow (HOF) as gait representation. Gait features are the fusion of real and synthetic FHEI. The CCR by 1-NN is 65.07% on USF HumanID gait database [35].

Support Vector Machines (SVMs) is one of the most effective classifiers which was introduced in the 1990s. SVM generally builds the optimal hyper-plane which has the maximum hyperplane margin or the maximum distance between the hyperplane and the nearest points of the pattern. The hyperplane which optimizes during the training process is used for binary pattern classification. However, SVM can be modified as a multiclass classifier which makes use of a one-against-one and one-against-all approach. SVM can deal with different types of pattern problems by optimizing its kernel setting such as linear, nonlinear and radial basis function. At the same time, it is not easy to choose a suitable kernel with its parameters in each dataset. SVM may use long training time for large dataset. And SVM result also lacks transparency because of the high dimensional model [56]. Same as k-NN, there are many publications using SVM such as Aggarwal and Vishwakarma [50] develop average energy silhouette image (AESI) and Zernike moment invariant feature. Gait features are extracted from the different fifteen fusion parts and each fusion parts features are training by SVMs. The CCR results are 91.47%, 89.7% and 84.67% on CASIA dataset B, OU-ISIR Treadmill B and USF HumanID gait database. Hanmin and Peiliang extract gait feature from the fusion of features between body contour feature, lower limb feature and dynamic regional variance feature. SVM and CASIA dataset B are chosen for the experiment. The CCR result is 96.82%[57]. Chetty et al evaluate several subspaces based on gait features extracted by PCA/LDA, and classifiers include Native Baythe es (NB), Multi-Layer Perceptron (MLP), SVM and Sequential Minimal Optimization (SVO). NB with LDA has the best CCR of 92.5% and 93.75% on CASIA dataset B and C, respectively. The result shows that SVM performance depends on its kernel. The best SVM CCR on CASIA dataset B and C are 81.13% and 86.25% using a linear SVM. [58]. Prakash et al use multi-model gait analysis including ANN, Random Forest (RF), LDA and RBF SVM for human identification. Eight features used include the number of frame per gait cycle, leg step area, swing ratio, height to width ratio at maxima, height to width ratio at minima, step length, foot length and centre of mass are used. The experiment dataset uses 10 subjects from the RAMAN lab and 30 subjects from CASIA dataset B. The CCR results are 75.0%, 53.3%, 56.7%, 63.3% and 93.3% using ANN, RF, LDA, SVM and multi-model ((RF+LDA)+SVM), respectively [59]. Bajwa et al identify a person by combining three classifiers of SVM, kNN and NN. The experiment uses a private dataset. The CCR results are 94.0%, 95.000% and 98.7% using NN, SVM and SVM+kNN+NN [60].

Deep learning, as an emerging machine learning technique, is adapted in gait recognition. It can be used as a feature extractor and classifier. This method is reported to have higher accuracy while it needs a powerful device and massive data, and has high computation. Many gait recognition research project use Convolutional Neural Network (CNN) which is a very popular deep learning method in this decade. For example, Yeoh et al extract deep features by CNN and compare two classifiers between SVM and CNN. The experiment tests on OU-ISIR Treadmill dataset B. The result shows that SVM with deep features (91.38%) has a higher classification rate than CNN with softmax classifier (87.80%) [61]. Shiraga et al develop GEINET which is the CNN designed for gait recognition with GEI. OU-ISIR large population dataset is used as gait database. GEINET outperforms in cross view experiments the generative approach and discriminative approach in a cooperative setting. It also outperforms with 89.7% CCR in uncooperative setting [62]. Alotaibi and Mahmood create specialized CNN architecture to improve gait recognition. CASIA dataset B is used as a gait database. When probe and gallery use the same appearance in 90°, the CCR results are 95.6%, 88.3%, 76.2% and 86.70% under normal waking, carrying a bag, wearing a coat and average CCR, respectively. When a dataset of 25 subjects in eleven views are used under unknown covariate condition, the CCR is 85.51% [63]. Rauf et al study the CNN knowledge transfer on gait recognition. A small fast fully connected network (FCN) is developed to retain the learning ability from the softmax weight matrix in large CNN. Then the FCN parameters are generated with gallery data. The CCR by CNN is 98.90%, 98.0%, 98.70%, 67.50% and 47.70% when a pair of gallery and probe sample is normal-normal, bag-bag, coat-coat, normal-bag and normal-coat, respectively. Retained knowledge FCN has a recognition rate of 87.60%, 85.90%, 91.70%, 50020% and 94.10% using the same pair of gallery and probe sample [64]. Some neural network are derived from CNN such as Multi-task Generative Adversarial Networks (MGANs). The proposed MGANs is the view-specific feature representations learning which preserves the view of temporal information during cross view recognition. GEI, CGI (Chrono-Gait Image) and PEI (Period Energy Image) are used as gait representation. OU-ISIR large population, CASIA dataset B and USF HumanID database are used as gait database. The CCR using PEI and MGANs are 93.1%, 74.6% and 94.7% on OU-ISIR, CASIA-B and USF dataset. The average CCR on CASIA dataset B and OU-ISIR without an identical view is respectively 74.6% and 79.8% using PEI and MGANs [65].

As it can be seen from the classification results, all classifiers have high CCR when they are used with the suitable gait feature and data reduction method. Additional, selected gait databases with different experiment sets also affect the classification rate.

Examples of model-free gait recognition publications in recent years are summarized in Table 2.1.

Table 2-1: Summary of recently model-free gait research

Method	Database	Performance (%)
AESI+ZNK+SVM[50]	CASIA-B OU-ISIR Treadmill B USF	91.47 72.7 72.53
GCF+MLDA(TCL)[66]	OU-ISIR-LP OU-ISIR dataset D USF	98.2 (All) 92.3 (high) and 91.2 (Low) 69
$P_{RW}D_{F}$GEI[55]	CASIA-B USF	82.0 58.0
NDM[67]	OU-ISIR-LP USF	98.1 (All) 61.1
2FInS [68]	CASIA-C OU-ISIR Treadmill A OU-ISIR Treadmill D	99 (fn) 97 (fs) 96 (fq) 78.02 100 (high and low)
PEI+MGANs[65]	CASIA-B OU-ISIR-LP USF	93.1 74.6 94.7
GEI+MGANs[65]	CASIA-B OU-ISIR-LP USF	93.2 70.1 93.3
SG[69]	CASIA-B	93.3
SMLDA (TCL)[70]	CASIA-B OU-ISIR-LP USF	72.45 98.2 73
Fusion (sum)[71]	CASIA-B CASIA-C OU-ISIR-LP TUM-GAID USF	94 99 98 90 94.4
GSP-CRC[72]	CASIA-B CMU MoBo	83.3 86.67
TGLSTM [73]	CAD-60 CASIA-B MSR-Action 3D TUMGAID	94.4 86.4 95.2 98.4
Deep CNN[74]	CASIA B	86.70
Deep CNN[63]	CASIA B	85.65 (uncooperative)
CT +PCANet[75]	USF	81.11
Gabor+SRKDA+SVM[76]	CASIA B	90.14
GOFI [77]	CASIA B CASIA C	98 (normal) 90 (bag) 64 (coat) 97 (normal) 88 (slow) 87 (quick)
GGEI+SVM[78]	CASIA B	90.4
CNN+SVM[61]	OU-ISIR Treadmill B	91.38
Siamese neural network[79]	OU-ISIR-LP	96.02 (All)
persistent homology[80]	CASIA B	88.6 (uncooperative)
ML-GCT[81]	CASIA B	75.34 (bag and coat)

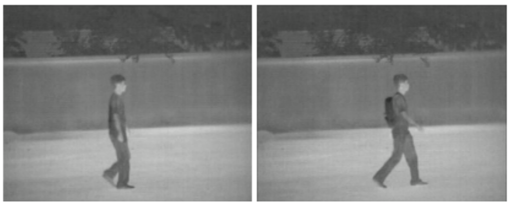
Method	Database	Performance (%)
Gabor+RSM-HDF[82]	USF OU-ISIR Treadmill B	81.15 90.72
GGI[36]	CASIA B SOTON small database	98.0 (90°) 100
SIGT+GLPP+NHC[83]	CMU MoBo OU-ISIR Treadmill A	95.46 75.39
GEI_{JSM} [84]	CASIA B USF	84.1 57.3
SDTTV[85]	USF	53
GII-SF[53]	CASIA B OU-ISIR Treadmill A OU-ISIR Treadmill B SOTON	98.0(Normal) 74.5(Bag) 45.0(Coat) 76.4(Ts4) 94.1(Ts5) 85.2(Ts6) 61.2 90.9(A) 86.3(B) 72.7(C)
TBP[86]	CASIA B CMU MoBo OU-ISIR Dataset D	90.8 96 99(high) 100(low)
GHGI[37]	CASIA B OU-ISIR Treadmill A	66.5 94.1(5km/h) 88.2(6km/h) 58.8(7km/h)
RBF network[87]	CASIA C CMU MoBo OU-ISIR Treadmill A	90.2(normal) 88.2(fast) 85.6(slow) 100(Fast) 96(slow) 85.3(5km/h) 91.2(6km/h) 97.1(7km/h)
FHEI-Fusion[35]	USF	65.07
SBDA+LDA[88]	CASIA B USF	78.20 61.35
GTDA+MMCA+LDA[89]	USF	57
RBL of GEI[90]	CASIA B	85.66 (90°)
Fusion of 5 parts on GEnI[51]	OU-ISIR Treadmill B	73.84
VI-MGR[91]	CASIA B	86.4(normal) 82.8(bag) 79.6(coat) (CVR) 100(normal) 89(bag) 76(coat) (90°) 99.5(normal) 69.6(bag) 87.1(coat) (CVR)

2.4 Gait Databases

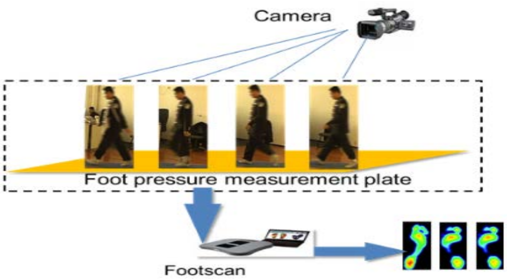
The major challenge in gait recognition is the recognition rate. However, there are various problems or conditions that affect gait recognition performance and accuracy. For example light emission (day/night), environment (indoor/outdoor), season (summer/winter), walking surface (grass/concrete, surface (flat/slope), dry/wet), projection (straight/curve), clothing (coat/skirt/jeans/shorts), shoe types (flip-flop/sandals/boots), carrying object (briefcase/bag/ backpack/staff) and camera view angles (frontal/side). Research may focus on different challenging topics. Many gait databases are created for supporting gait recognition research in various sonditions.

Several gait databases based on the organization which usually uses in gait recognition research are listed below with their characteristics.

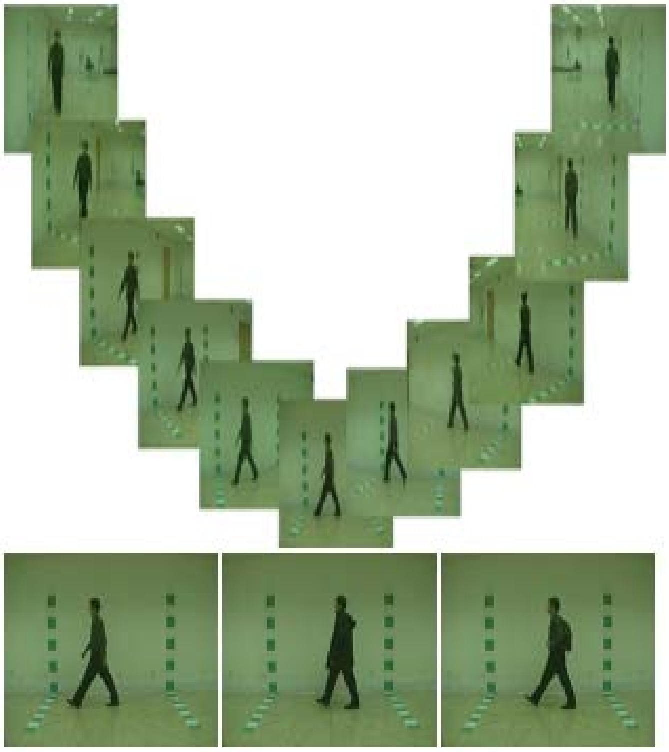
(a) Dataset A



(c) Dataset C



(d) Dataset D



(b) Dataset B

Figure 2-13: CASIA gait database [92]

1) CASIA Gait database – The Institute of Automation, Chinese Academy of Sciences provides this database for gait recognition and related research. There are four datasets as show in Figure 2-13 [92, 93].

   a. Dataset A which also calls NLPR (National Laboratory of Pattern Recognition) was created on 10 December 2001. There are twenty subjects. Each person is captured in three view angles including 0°, 45° and 90° to the image plane. Each direction is captured three times. Twelve image sequences are provided for each person. The lengths of the sequences are between 37 to 127 images. This dataset provides both video files and silhouette files.

   b. Dataset B was created in January 2005. There are 124 subjects in 11 view angles from 0° to 180°. There are 18° different between adjacent view angles. Each subject is captured in three variations including 6 normal walking, 2 wearing a coat and 2 carrying a bag. In total ten videos per subject are captured. This dataset provides video files, silhouette files and GEI files. GEI in MATAB format is also provided.

c. Dataset C was created in June-August 2005. All videos are captured by the infrared (thermal) camera in the nighttime. There are 153 subjects in the dataset. Four walking conditions namely normal walking, fast walking, slow walking and walking with a bag are captured. This dataset provides video files and silhouette files.

d. Dataset D was created in July-August 2008. Eighty-eight Chinese people were captured indoor by the camera and Rscan Footscan. The background scene is the real surveillance scenes. This dataset focuses on the behaviour of biometrics and its corresponding prints. There are two variations: normal walking and carrying a bag. Two different walking speeds are captured. This dataset provides silhouette files, footprint files, static cumulative foot pressure image and walking pose sequence images files and foot pressure dynamic data in MATLAB file.

2) Southampton university currently provides two main databases [94].

a. HiD gait database is the former Human ID at a Distance Database or Soton database. This database ever provides two size databases including large and small databases. Currently, HiD gait database provides only the large database.

- The large database is created in summer 2001. There are approximately 100 subjects in a normal condition which are captured in three scenarios: indoor, outdoor and treadmill. Each scenario has two views: side view and oblique view. All subject walks in a laboratory environment (chromakey scene).
- The small database challenges under various conditions include carrying various bags, wearing different clothes or footwears. However, only twelve subjects are captured inside track with a green chromakey backdrop. They are also captured at a different speed.

b. Multimodal is a multi-biometric database that captures gait, face and ear videos. There are over 400 subjects recorded by 12 cameras in a biometric tunnel.

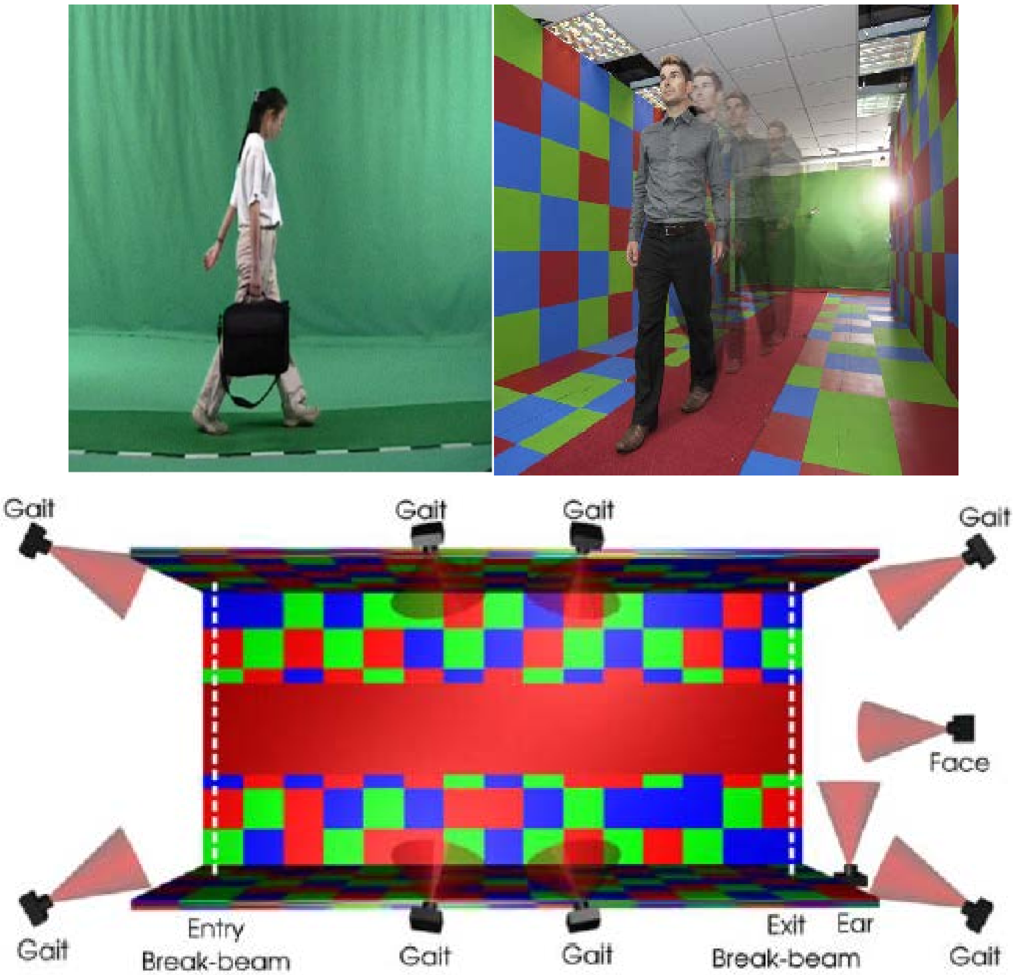
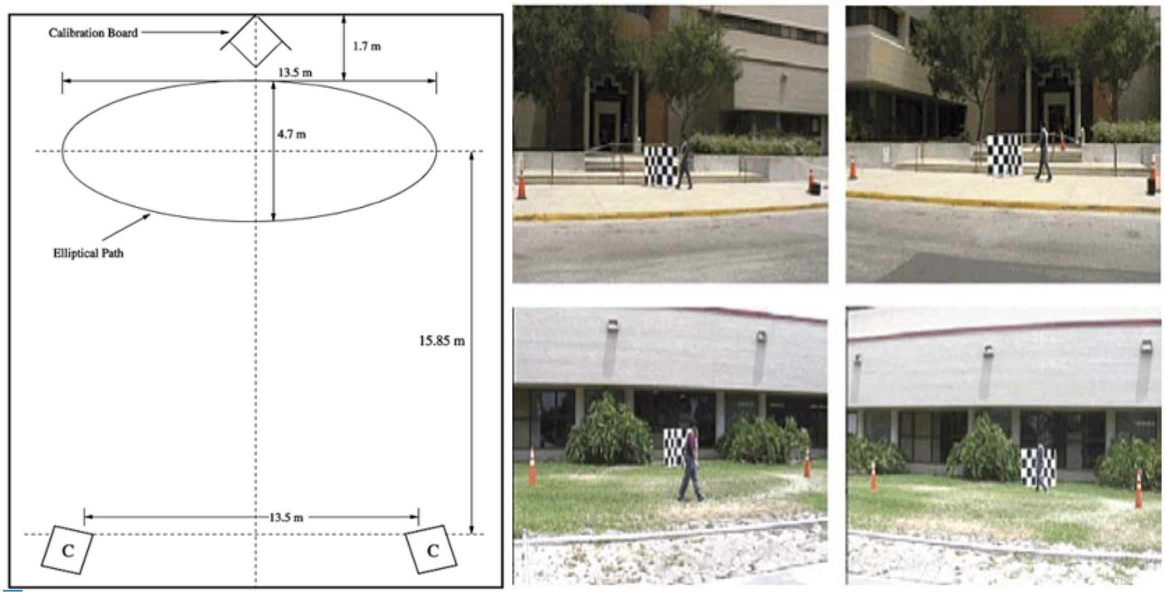


Figure 2-14: Southampton gait database

3) USF HumanID dataset was created by the University of South Florida between May 20-21, 2001 and November 15-16, 2001. Each subject walks counterclockwise around anelliptical course as shown in Figure 2-15. Two outdoor courses are set for video recording. After the update, there are 122 people in five different covariates: shoe types (A and B), with or without carrying a briefcase (BF and NB), grass and concrete surface (G and C), left and right viewpoints (L and R), and 2 different time instants (May and November). There are 32 possible conditions under all covariance however, not all persons are captured in all conditions. This dataset provides video files, sample sequence files, computed silhouettes files and source code [10].



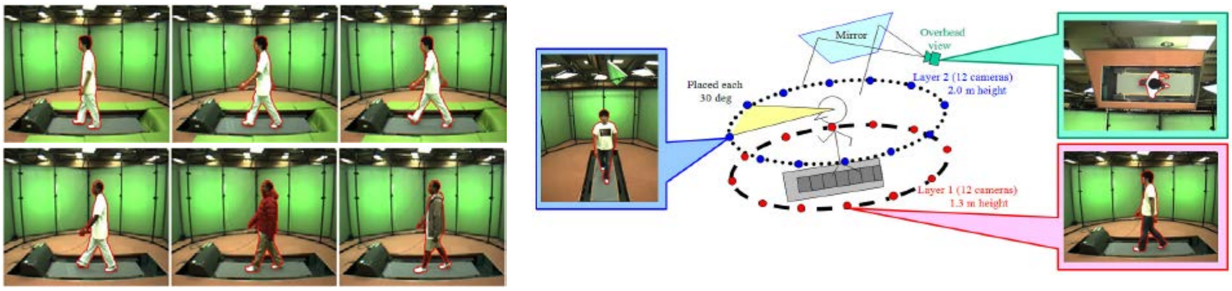
	May 2001				Nov 2001				
	No Briefcase		Briefcase		No Briefcase		Briefcase		
	Concrete	Grass	Concrete	Grass	Concrete	Grass	Concrete	Grass	
Shoe A	C,A,L, NB	G,A,L, NB	C,A,L, BF	G,A,L, BF	C,A,L, NB	G,A,L, NB	C,A,L, BF	G,A,L, BF	Left Camera
B	C,B,L, NB	G,B,L NB	C,B,L, BF	G,B,L, BF	C,B,L, NB	G,B,L NB	C,B,L, BF	G,B,L, BF	Left Camera
A	C,A,R, NB	G,A,R, NB	C,A,R, BF	G,A,R, BF	C,A,R, NB	G,A,R, NB	C,A,R, BF	G,A,R, BF	Right Camera
B	C,B,R, NB	G,B,R, NB	C,B,R, BF	G,B,R, BF	C,B,R, NB	G,B,R, NB	C,B,R, BF	G,B,R, BF	Right Camera

Figure 2-15: USF HumanID dataset

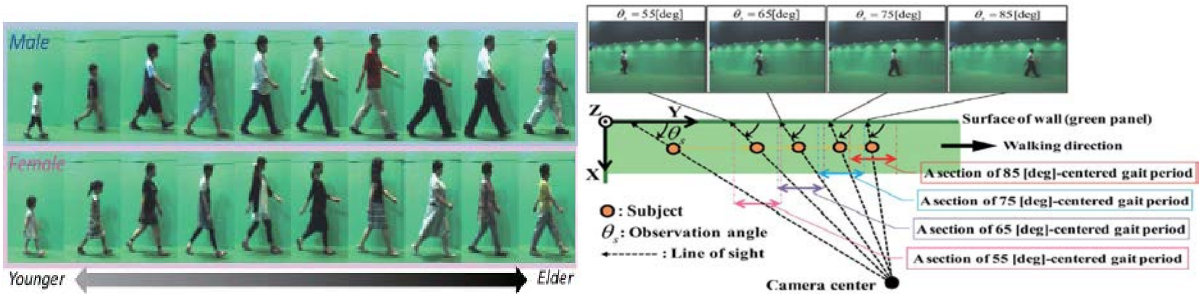
4) OU-ISIR Biometric database is provided by the Institute of Scientific and Industry Research, Osaka University. There are currently eight different datasets as follows.

   a. Treadmill dataset is created since March 2007. Each subject walks on a treadmill surrounded by 25 cameras. There are four sub-dataset, however, three sub-dataset except dataset C is currently available on their website[95].

      - Treadmill dataset A contains data from 34 subjects with speed variation from 2km/h to 10 km/h with a speed interval of 1 km/h. All video is captured from a side view.

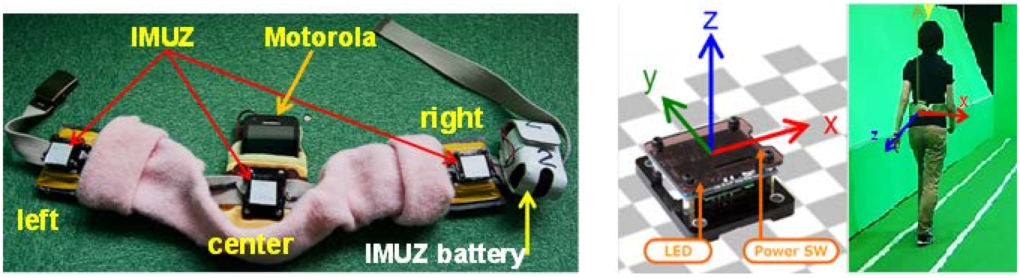


(a) Treadmill dataset

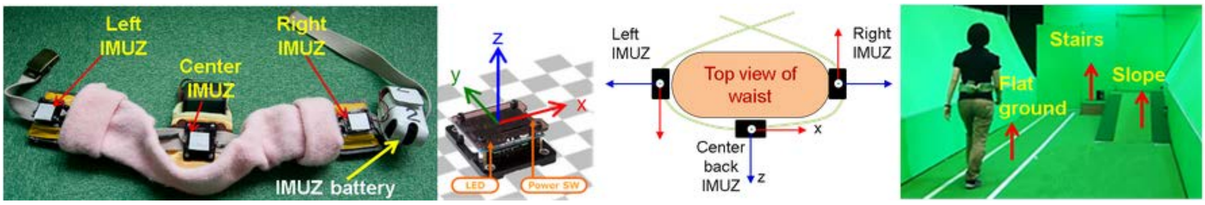


(b) Large population dataset

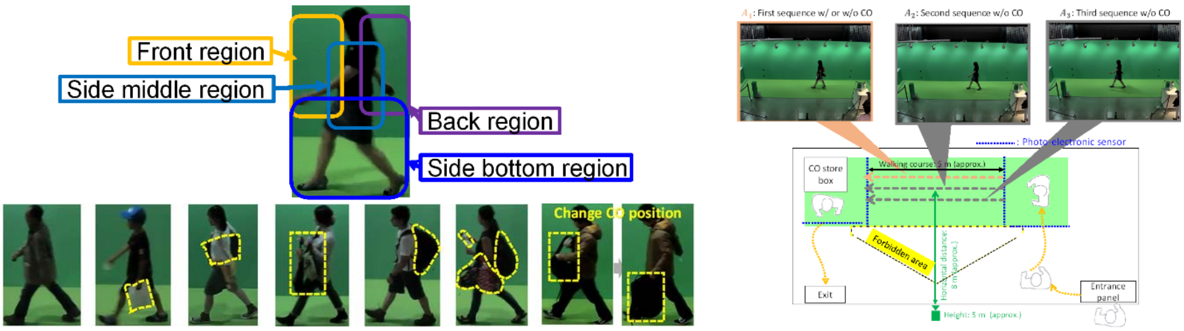
(c) Speed transition dataset



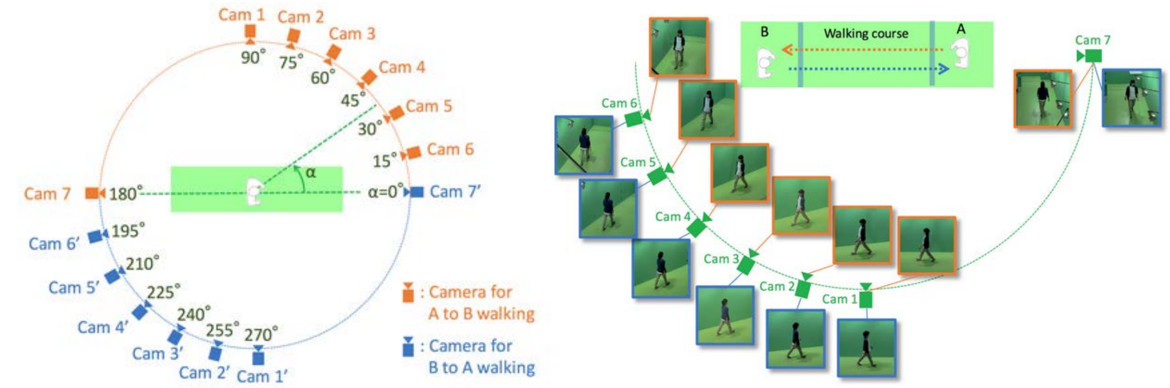
(d) Inertial sensor dataset



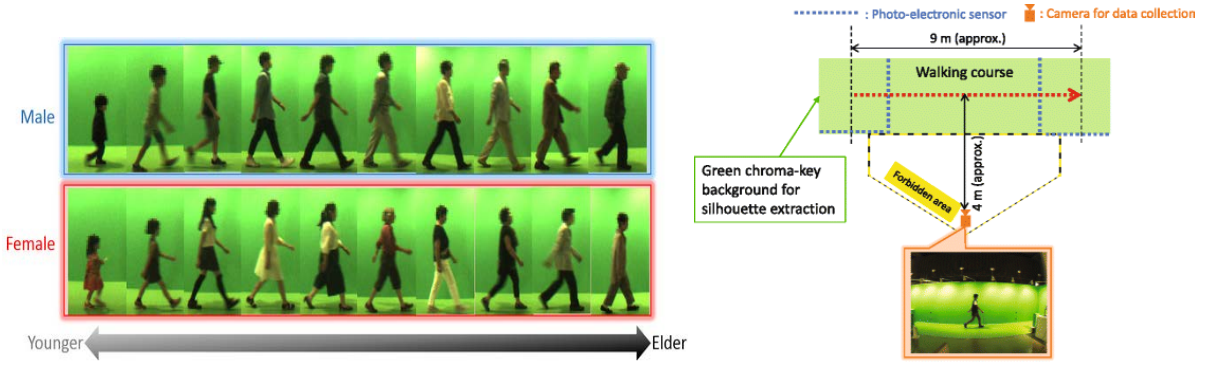
(e) Similar action inertial sensor



(f) Large population dataset with Bag



(g) Multi-view large population dataset



(h) Large population dataset with age

Figure 2-16: OU-ISIR gait database

- Treadmill dataset B contains data from 68 subjects with clothes variation up to 32 combinations. All subject is captured from a side view.
- Treadmill dataset C contains data from 200 subjects (100 females and 100 males) with age range 4 to 75 years old and 25 views.
- Treadmill dataset D contains data from 185 subjects with various degrees of gait fluctuations over a number of the period such as differences in the same phase across the period. All subjects are captured from a side view.

b. Large population dataset is collected since March 2009. Over 4,000 subjects are captured with age variation from 1 to 94 years old. This dataset is captured indoor with real-life clothing by two cameras, however, only the top camera produced data available to the public. The top camera can rotate thus each subject is captured under four different viewpoint namely 55°, 65°, 75° and 85° [96].

c. Speed transition dataset is divided into two datasets. Each dataset was collected two group data (probe and gallery) under different conditions[97].

   - Dataset 1 contains data in the indoor environment. Probe collected data about 26 subject which walks toward the setting poster then gradually reduce walking speed until the stop at the finish point. While the gallery collects 179 subjects including 26 probe subject with the constant walking speed of 4 km/h on the treadmill or nearly constant speed on the ground.
   - Dataset 2 contains data on the treadmill. Probe collects 25 subjects twice on the treadmill which automatically changes speed with a pair of acceleration from 1 km/h to 5 km/h and deceleration from 5 km/h to 1 km/h. Gallery collects 178 subjects including 25 subjects in the probe with the constant walking speed of 4 km/h.

d. Inertial sensor dataset was collected data with w 3 IMUZ sensors and 1 smartphone in 2011. Each IMUZ includes a triaxial accelerometer and gyroscope while smartphone includes only a triaxial accelerometer. 6D gait singles are collected in total from both sensors types. Data captureed on a level walk, up-slope and down-slope walk condition. The data validation is not equal for all subjects. Thus the data collection is divided into two datasets to maximize the number of subjects and maximize the variation of sensor location, ground condition and sensor type[98].

   - The first dataset contains level walk data of 744 people (389 males and 355 females) with ages ranging from 2 to 78 years by central IMUZ sensor. Each subject is captured in two different levels walk-which is automatically extracted by motion trajectory constraint and signal autocorrelation
   - The second subset contains 495 people with three IMUZ sensors and 408 people with a smartphone. Each subject is captured two level walk sequence, an up-slope walk sequence and a down-slop walk sequence. Additionally, each data is captured from sensors and simultaneous videos.

e. Similar action inertial dataset was captured in 2011. Two main purposes of this dataset are the inertial sensor-based action recognition evaluation and the robustness of the sensor orientation-inconsistent evaluation. Gait information of 460 people are collected with similar gender ratio and age ranging from 8 to 78 years old. There are five actions: walking on flat ground, up/down stairs and up/down slope[20].

f. Large population dataset with Bag was collected 62,528 subjects with the age range of 2-95 years old. All subjects use their own carrying objects and they walk with the preferred speed. Each subject is captured three times in the straight walking course. The first sequence walks with or without carrying an object (he/she did or did not carry an object). In the second and the third, it captured people walk without carrying objects. The β version dataset (OU-LP-Bag β) that published in 2017 has 2070 subjects with two sequences. One sequence is people who walk with their own carrying objects and the other captures people who walk without carrying objects[99].

g. Multi-view large population dataset collected 10,307 subjects (5,514 males and 5,193 females) from 14 view angles ranging 0° to 90° and 180° to 270° with 15° view interval. Each subject is captured by 7 cameras when they walk forward and backwards on the scene. Totally, 28 gait image sequences (7 view angles camera x 2 forward and backward x 2 repeat walking) are captured per each subject[100].

h. Large population dataset with age collects 63,846 subjects (31,093 males and 32,753 females) with age ranging from 2 to 90 years old. Each age group from 0 to 7 years old with a 5-year interval contains more than 500 subjects. Silhouette has high quality and information correctness[101].

2.5 Conclusion

Gait is a soft biometric which recognizes a personal characteristic, by the way their walk such as sex, gender, age, weight, height and body mass index. However, almost all gait research focuses on personal identification. Gait recognition input is usually captured by a video which can be processed with two approaches including model-based and model-free. Currently, the model-free approach has been used more than a model-based approach because it is simpler, lower cost and more suitable for the real-world environment. Additional, many standard gait databases also uses Gait Energy Image (GEI) which is the common model-free gait representation as their gait representation. Moreover, some standard gait database provides the GEI files for their own database.

Gait recognition is extensively studied in the last decade as it can be seen from the reviewed example and the summary of recent publications in Table 2.1. The performance or correct classification rate (CCR) in each research is quite high especially the CCR on CMU MoBo, CASIA dataset C, SOTON small database and OU-ISIR-LP by the identical view. The problem based on gait database can be summarized as follows. USF HumanID gait database has much lower correct classification rate under surface and time condition which affect the averaged classification rate. OU-ISIR Treadmill A has lower classification under speed variation which identifies individuals from different walking speed. OU-ISIR Treadmill B has a lower recognition rate under clothing variation. OU-ISIR-LP has a lower recognition rate under the cross view recognition. CASIA dataset B has a lower recognition rate under appearance changes (carrying a bag and wearing a coat), cross views recognition and view angle recognition.

If the problem is grouped together, there are two common problems which usually affect the classification rate. First is the apparent change in OU-ISIR Treadmill B and CASIA dataset B. Second is the view classification and cross view classification in OU-ISIR-LP and CASIA dataset B. This indicates that both problems are usually solved in gait recognition. Thus the CASIA dataset B which covers both problems is chosen as the main gait database in this study. However, CASIA dataset B collect data from 124 subjects which are considered as a small dataset. Thus the second dataset should be a large population dataset. Thus the OU-ISIR Large population dataset with a bag which recently published is chosen as second gait database to verify the proposed gait representation and framework on large-scale data.

The correct classification rate (CCR) which is published by recent related research is demonstrated and summarized in Table 2.2, 2.3 and 2.4. CASIA dataset B has 10 gait sequences per person including six normal walking, two of walking with a coat and two of carrying a bag. In Table 2.2, four samples from normal walking datasets are used as gallery samples for training and the rest are used as probe samples for testing. The result focuses on lateral view or 90° In Table 2.3, the result focuses on the average CCR over eleven view angles and the training and testing set is the same as those used for Table 2.2. OU-LP-Bag dataset that is currently the largest dataset with object carrying is recently published in 2017. The current recognition rate under this dataset is shown in Table 2.4 and Table 2.5.

Table 2-2: lateral view (90°) CCR on CASIA dataset B

Method	Normal	Bag	Coat	Average
Baseline TM (NN) [102]	97.60	52.00	32.70	60.77
GEI [32]	99.60	57.20	23.80	60.20
Pair-wise+CDA [103]	**100.00**	78.30	44.00	74.10
iHMM[104]	94.00	45.20	42.90	60.70
GPPE[105]	93.36	56.12	22.44	57.31
RF-based mask BSS[106]	98.80	73.80	63.70	78.77
STIPs[107]	95.40	60.90	52.00	69.43
Deterministic learning[39]	98.40	93.50	90.30	94.07
GII-SF [53]	98.00	74.50	45.00	72.50
SG[69]	98.40	86.70	**94.80**	**93.30**
Two-phase VI-MGR[91]	**100.00**	89.00	76.00	88.33
Feature selection mask[108]	95.97	63.39	72.77	77.38
EnDFT[40]	97.61	83.87	51.61	77.70
Unsupervised feature selection[109]	95.56	74.11	86.61	85.43
Persistence homology[80]	94.10	84.20	87.60	88.60
SD+GLPP[110]	98.80	70.10	89.29	86.06
Modified phase [111]	93.60	81.70	68.80	81.40
VI-MGR[46]	98.39	75.89	91.96	88.75
Sparse Dictionary Learning[112]	98.40	86.70	**94.80**	93.30
Fusion(sum)[71]	96.00	**94.00**	92.00	**94.00**

Table 2-3: average CCR over eleven view angles on CASIA dataset B

Method	Normal	Bag	Coat	Average
Baseline[102]	97.70	67.80	28.90	64.80
GEI [32]	93.10	48.80	18.80	53.56
GEnI [33]	98.30	80.10	33.50	70.63
optical flow fields[113]	97.50	83.60	48.80	76.60
CGI [114]	99.07	68.52	42.59	70.06
Masked-GEI CDA[106]	98.57	77.78	86.46	87.60
STIPs+BoW [115]	94.50	60.90	58.50	71.30
Deep CNN[74]	95.60	88.30	**86.20**	86.70
ML-GCT[81]	n/a	**96.74**	81.67	89.20
GEI_{JSM} + RM1[84]	97.20	91.20	63.30	83.90
GII-SF[53]	98.00	74.50	45.00	72.50
GOFI [77]	98.00	90.00	64.00	84.00
$P_{RW}D_{F}$GEI[66]	98.40	88.70	58.90	82.00
SMLDA (TCL)[70]	98.80	38.38	82.18	72.45
GSP-CRC[72]	99.00	80.70	70.20	83.30
AESI+ZNK [50]	**100.00**	93.10	81.30	**91.47**
TGLSTM [73]	86.10	87.80	85.20	86.40

Table 2-4: Baseline on OU-ISIR Large Population dataset with Bag [99]

Benchmark	Rank-1		Rank-5		z-FRR1%		z-EER		z-AUC	
	Coop	Uncoop	Coop	Uncoop	Coop	Uncoop	Coop	Uncoop	Coop	Uncoop
DM	17.7	15.9	23.4	20.5	56.3	68	18.5	29.9	10.1	23.2
PCA_LDA	40.8	31.4	53	41.3	21.2	34.3	7.4	14.4	2.4	8
GERF	38.5	31.2	50.9	42.2	30.6	34.6	8	11.4	2.7	5.1
RSVM	24.7	18.3	35.6	27.6	34.1	43.9	9.6	14.7	3.5	8.2
GEINet	22.3	18.5	32.5	26.9	34.8	43.3	11.3	14.7	4.5	7.1
SIAME	**49.8**	**50.3**	**69.7**	**70.5**	5.7	5.4	2.5	2.4	0.3	0.3

Table 2-5: the classification rate on OU-ISIR Large Population dataset with Bag β version [116]

Method	z-EER	Rank-1
GEnI	18.82	29.5
Masked GEI	61.95	0.1
Gabor GEI	10.48	46.4
GEI w/o ML	19.59	24.6
GEI w/o LDA	8.1	54.6
GEI w/ 2DLDA	11.47	43.3
GEI w/ Ranking SVM	10.81	28.3
JI-ML w/ Ranking SVM	5.45	57.4

Chapter 3 Gait Recognition Framework and Gait Representations

This Chapter presents the basic gait recognition framework. The general framework for a gait recognition system is shown in Figure 3.1. This system has two phases, training and testing. In the training phase, the first process is background subtraction which separates foreground or interesting objects from the background or uninteresting objects. Next, processed sequence images are used to generate gait representation which is a gait compact image in this study. Feature extraction is followed to select the important information from gait representation. Then personal models are generated from selected gait features by training with a chosen classifier. In the recognition or identification phase, all processes are similar to those in the training phase. Nonetheless, the last stage in the recognition phase is the prediction process which calculates the similarity score between a testing sample and personal models to make a decision. The highest score among the personal models is chosen as the recognition result from this system.

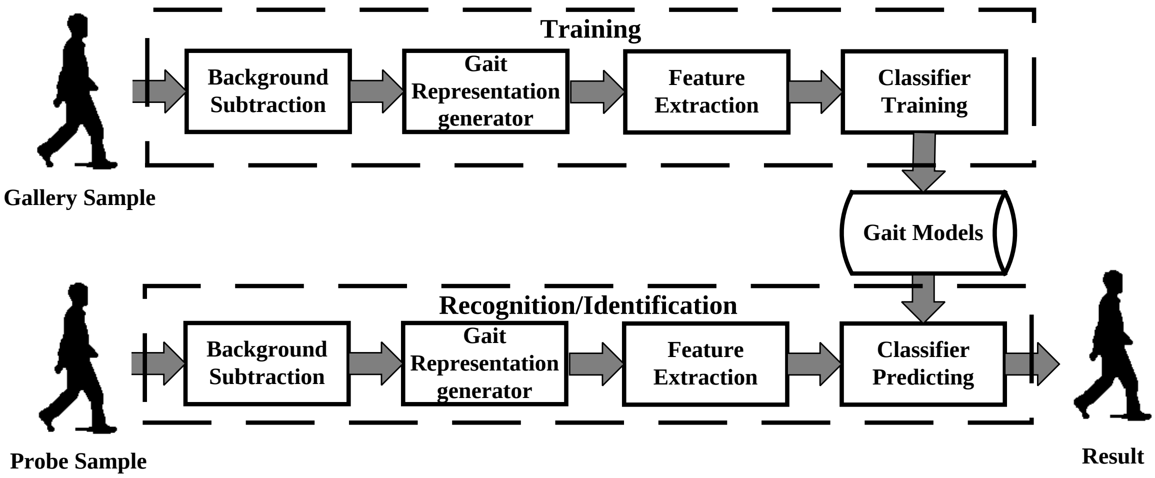


Figure 3-1: General Gait Recognition System Overview

Section 3.1 introduces the gait recognition system with its configuration related information. Section 3.2 presents gait representations which are the main focus of this study. Section 3.3 shows experimental results which examine the potential of the gait recognition system and gait representations. A Chapter summary is given in Section 3.4.

3.1 Gait Recognition Framework and Configurations

The general gait recognition framework is shown in Figure 3.2. The training phase creates personal models from extracted gait features. In model-free gait recognition, gait features are selected from gait representation which is generated from ฟ sequence น ด gait images. A generated gait representation which normally presents complete gait cycle information may be directly used as the training input to a classifier. The prediction process compares the testing sample with all existing gait models to make the decision with the highest score in similarity.

In Chapters 3 to 5, CASIA gait dataset B is chosen as the gait database for all experiments[117]. This dataset provides both raw video sequences and ground truth image sequences. This study uses the image sequences which are already processed by the background subtraction process as the system input. Four important processes are involved in the study: gait representation generation, gait feature extraction, personal model creation in the training phase and prediction in the testing phase. The first process generates the gait compact image that combines the provided image sequence into a single image. Four gait representations, GEI (Gait Energy Image), GEnI (Gait Entropy Image), GGI (Gait Gaussian Image) and GGEnI (Gait Gaussian Entropy Image) have been created and tested in this Chapter. The feature extraction is done by Principal Component Analysis (PCA) which reduces the data dimension by principal component coefficients. These coefficients are used as personal gait features as the input to Support Vector Machine (SVM), a classifier in both the training and identification phases. SVM is chosen as the main classifier in this research, nonetheless, simplest Nearest Neighbor (NN) is also compared with SVM in the preliminary experiment. The gait recognition system for the study is shown in Figure 3.2. Details of all related information are explained in this section.

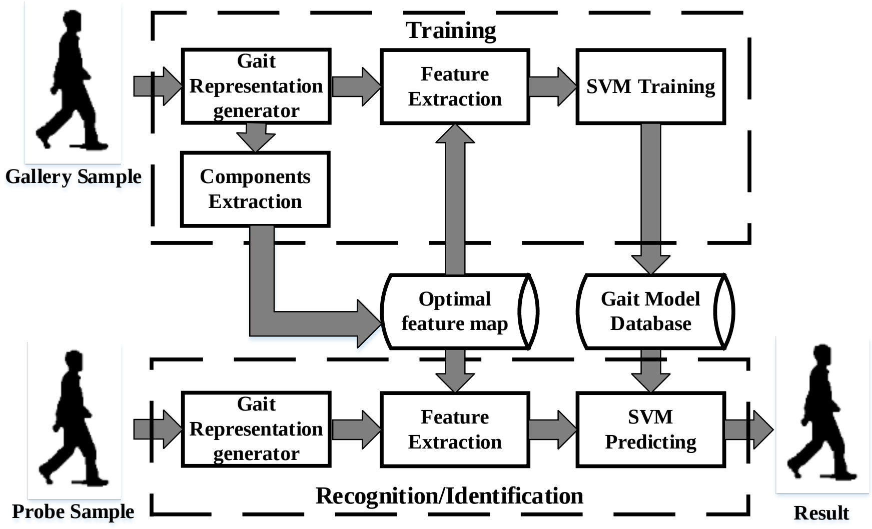
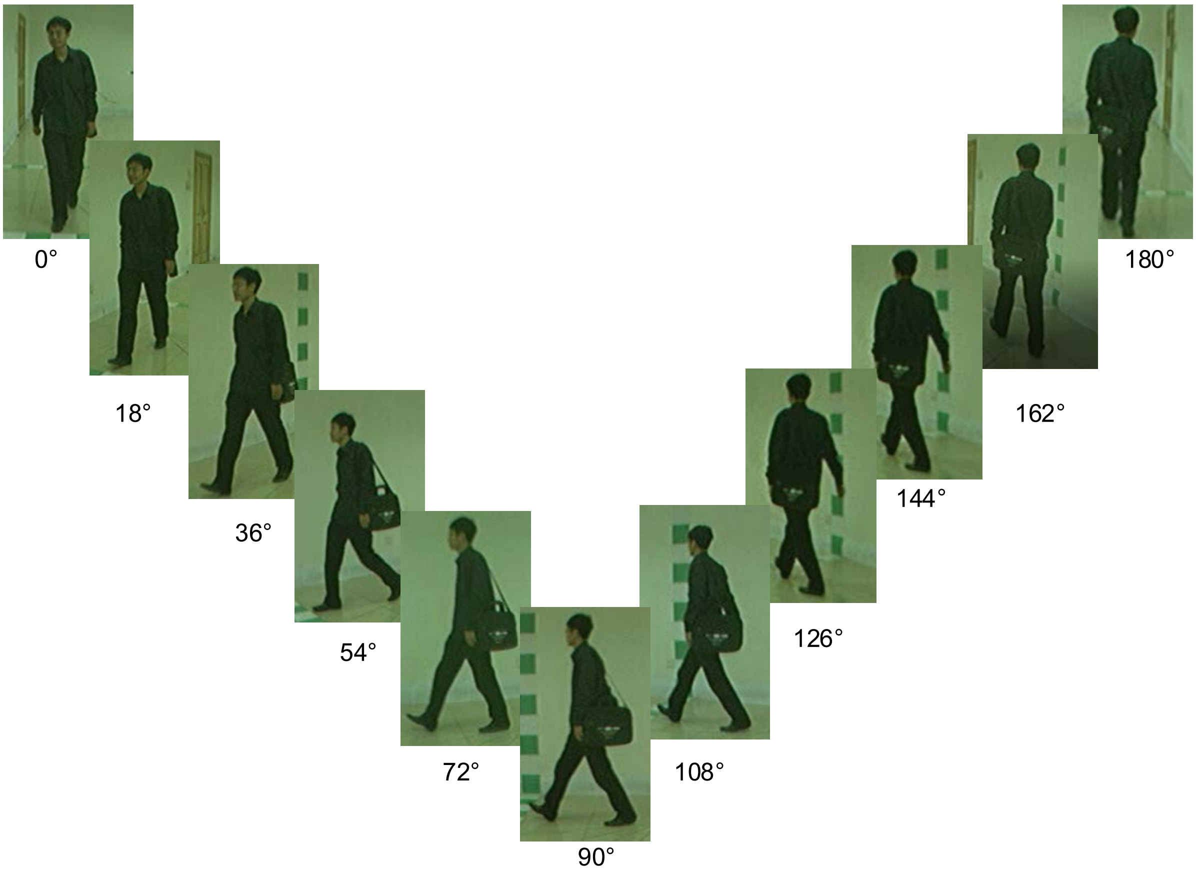


Figure 3-2: Gait Recognition System Overview

3.1.1 CASIA gait dataset

The Chinese Academic of Sciences, Institute of Automation (CASIA) provides the databases for gait recognition and related research. There are three datasets included, which are dataset A (former), dataset B (Multiview) and dataset C (infrared). In this research, dataset B which was created in January 2005 is chosen as the main testing dataset in Chapter 3 to 5 for the following reasons: each subject had multiple appearances, multiple camera view angles and a number of samples per each subject.

Dataset B had collected gait video sequences from 124 people who walked past 11 cameras with different view angles from 0 to 180 degrees. Each person was captured ten times with three variations: 6 normal walking videos, 2 wearing a coat videos and 2 carrying a bag videos. In total, there were 13640 videos (124 person x 11 view angles x 10 videos in three variations). An example of this dataset can be seen in Figure 3.3. In the case of normal walking, they used normal clothing with little effect on the human silhouette and women did not wear a skirt, dress or other types of clothing which obstructed their silhouette shape. In this dataset, bags were two styles including messenger bags and satchels, but carrying position was dependent on each person. While coats were of various types, each person had their own coat. This made more variation in walking with coat appearance in the dataset.



(a) View Angles

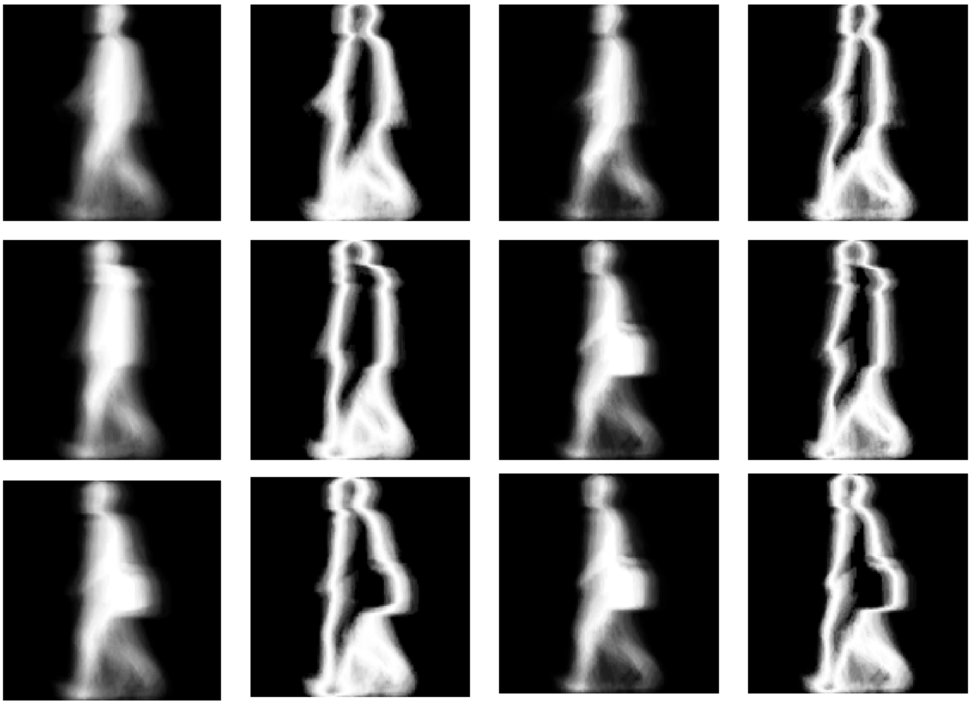
(b) Appearances

Figure 3-3: Example of CASIA gait dataset B

CASIA also provided the ground truth image sequences for all videos in dataset B. This research used these provided image sequences to generate gait representations. Due to the fact that only 116 persons in the dataset have provided image sequences for every view angle this research used only the 116 persons' data in experiments.

3.1.2 Gait representations

The basic and simplest gait compact image is an average gait image or Gait Energy Image (GEI)[32] which is popular and well-known in the gait recognition community. There have been many developed gait representations in this decade e.g. Gait Information Image[53], Flow Histogram Image[35] and Gait Optical Flow Image[77]. Among them are Gait Entropy Image (GEnI) and Gaussian Gait Image (GGI) which uses entropy and Gaussian techniques to generate compact gait images, respectively. A newly combined gait representation named Gait Gaussian Entropy Image (GGEnI) is created in this research. The examples of four gait representations are shown in Figure 3.4.



a) GEI b) GEnI c) GGI d) GGEnI

Figure 3-4: Example of gait representations in different appearance covariance

3.1.2.1 Gait Energy Image (GEI)

Gait Energy Image (GEI) is the common model-free gait representation. The average silhouette image, calculated by averaging all binarized silhouette images from complete gait cycle as it can be seen in

Figure 3.5, is the basic gait representation as grey level image. This technique increases noise tolerance and reduced memory space. GEI is defined as:

$$G(x, y) = \frac{1}{N}\sum_{t=1}^{N} B_t\,(x, y) \tag{3.1}$$

where *N* is the number of silhouette frames in walking sequence, *t* is the frame number in the walking sequence and $B_t(x, y)$ is the density value at pixel coordinate *(x, y)* in a frame *t* [32].

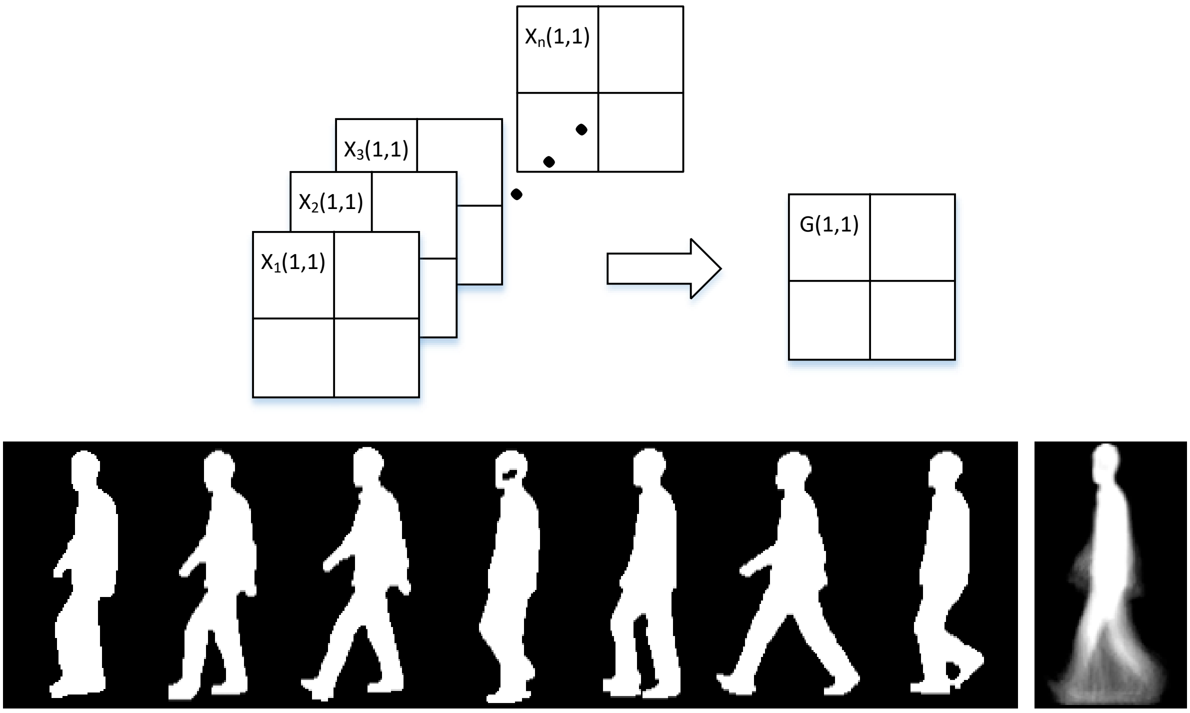


Figure 3-5: Gait Energy Image Generator

3.1.2.2 Gait Entropy Image (GEnI)

This technique aims to limit unnecessary appearance information or no movement area in motion images. Thus, it is more robustness to appearance changes. Same as GEI, sequential silhouette images of personal gait cycle are used as an input which calculates Shannon entropy technique using equation (3.2).

$$G_{GEnI}(x, y) = \sum_{k=1}^{K} p_k(x, y) - log_2 p_k(x, y) \tag{3.2}$$

where x, y is pixel coordinate and $p_k(x, y)$ is the k^{th}probability which have $K = 2$ because original input images are a binary image. However, the output is the grey scale image. This study follows the basic concept in [33]. Therefore $p_2(x, y) = G(x, y)$ in equation (3.1) and $p_1(x, y) = 1 - p_2(x, y)$.

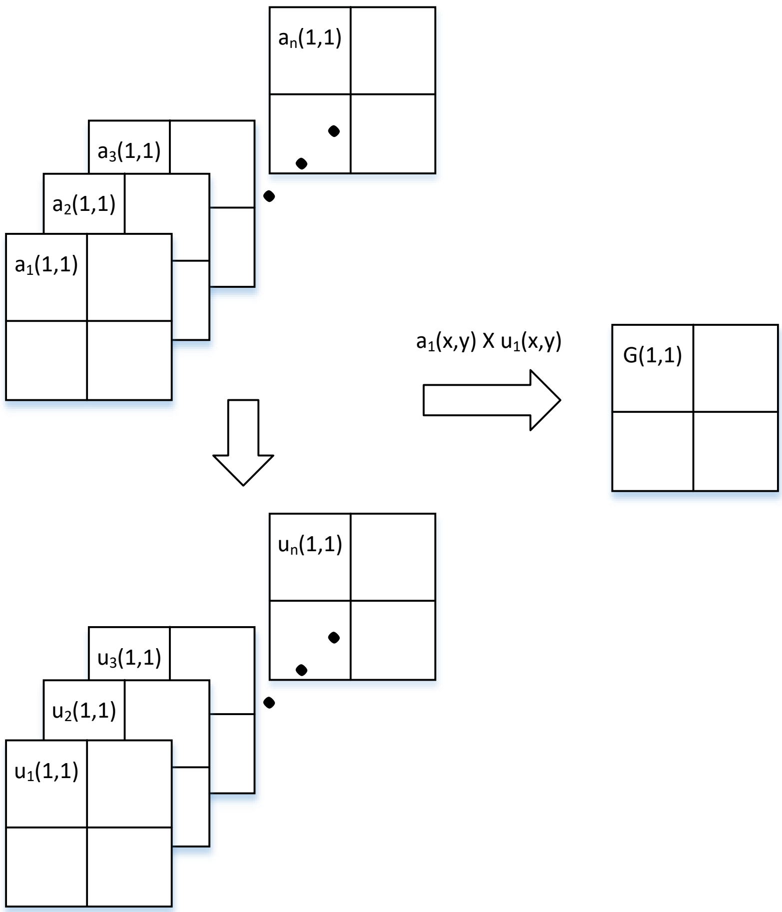


Figure 3-6 Gait Gaussian Image Generator

3.1.2.3 Gait Gaussian Image (GGI)

GGI is similar to GEI, however, it uses a Gaussian function instead of the average function[36]. It reduces the noise effect from the individual frame in the complete gait cycle. The Gaussian function is defined as follows:

$$u_i(x, y) = e^{-\frac{(a_i(x,y) - \overline{a(x,y)})^2}{2\sigma^2}} \tag{3.3}$$

where $u_i(x, y)$ is Gaussian membership at pixel (x, y) in i^{th} frame, $a_i(x, y)$ is the respective pixel (x, y) of i^{th} frame, $\overline{a(x, y)}$ is the mean of the respective pixel (x, y) in every frame and σ is the standard deviation of pixel vector. The Gaussian member is calculate for each frame in gait cycle as can be seen in Figure 3.6.

Then the output pixel $G(x, y)$ is calculated from the average of the multiplied result between the corresponding pixel and Gaussian membership, as shown in equation (3.4).

$$G_{GGI}(x, y) = \frac{1}{N} \sum_{i=1}^{N} a_i(x, y) \times u_i(x, y) \tag{3.4}$$

where $b(x, y)$ is the output as pixel position (x, y) and *N* is the number of silhouette frames in walking sequence

3.1.2.4 Gait Gaussian Entropy Image (GGEnI)

The aim of this newly purposed gait representation is for improving robustness against appearance changes in GGI, thus, the GEnI concept is applied with GGI in this representation. GGEnI is calculated with equation (3.2), with the probability function changing to Gaussian membership function.

GGEnI is defined as:

$$G_{GGEnI}(x, y) = \sum_{k=1}^{K} p_k(x, y) - log_2 p_k(x, y) \tag{3.5}$$

$$u_i(x, y) = e^{-\frac{(a_i(x,y) - \overline{a(x,y)})^2}{2\sigma^2}} \tag{3.6}$$

$$p_2(x, y) = \frac{1}{N} \sum_{i=1}^{N} a_i(x, y) \times u_i(x, y) \tag{3.7}$$

$$p_1(x, y) = 1 - p_2(x, y) \tag{3.8}$$

where x, y is pixel coordinate, and $p_k(x, y)$ is the k^{th}probability, $u_i(x, y)$ is Gaussian membership of i^{th} frame, $a_i(x, y)$ is pixel value of i^{th} frame, $\overline{a(x, y)}$ is the mean of (x, y) coordinate in every frames, σ is the variance of pixel vector and $p_k(x, y)$ is the k^{th} probability.

All gait compact image can be used as gait features. However, the full gait compact image size may be too big for classifier training process. It uses more time and computional cost to generate personal gait models. Many research reduces the data dimention with various technique such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA). In this study, PCA is chosen. However, the gait compact image is reformatted into flat vector before the data reduction process.

3.1.3 Principal Component Analysis

PCA or Karhunen-Loeve (KL) transformation is a statistical technique which has been widely used to reduce data dimensions in pattern recognition and computer vision. It is also used to select the important information or features in image processing. There are four steps for optimal feature map creation by PCA. Firstly, data matrix *X* is created from image vectors that are represented as a set of training GEI *I*. The average vector in $\bar{I}$ is consequently computed and subtracted from each column in matrix *X*.

$$X = \begin{bmatrix} \begin{bmatrix} \cdot \\ \cdot \\ \cdot \\ i_1 \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \begin{bmatrix} \cdot \\ \cdot \\ \cdot \\ i_2 \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \dots \begin{bmatrix} \cdot \\ \cdot \\ \cdot \\ i_n \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \end{bmatrix} \tag{3.9}$$

$$i_1,\ i_2, \dots ,\ i_n\ \in I - \bar{I} \tag{3.10}$$

Secondly, the covariance matrix *C* is computed from the training matrix *X* by the following formula

$$cov(X, Y) = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})}{n-1} \tag{3.11}$$

$$C^{n \times n} = (c_{i,j}, c_{i,j} = \ cov(X_i\ , X_j)) \tag{3.12}$$

where $C^{n \times n}$ is the covariance matrix with n rows and n column and X_i is the i^{th} data.

Thirdly, the eigenvector matrix V and diagonal eigenvalue matrix λ are computed from the covariance matrix C.

$$C \times V = \lambda \times V \tag{3.13}$$

Finally, some eigenvectors in matrix V are chosen as the principal component matrix P in order from the highest eigenvalues in matrix λ. Then, matrix *P* is normalized as the eigenvectors of the covariance matrix. After that, the optimal feature map, matrix *M*, is created from the chosen eigenvectors matrix *P* and data matrix X.

$$M = P \times X \tag{3.14}$$

The optimal feature map is multiplied with input data to reduce the input data dimension. The reduced data is used as gait features for classification processes by SVM.

3.1.4 Support Vector Machines

SVM is a binary classification method which is used to classify objects into two classes. SVM basically calculates the Optimal Separating Hyperplane (OSH) which focuses on the edge of the class distribution in training cases. An example of support vectors in linear hyperplanes is circled as it can be seen in Figure 3.7.

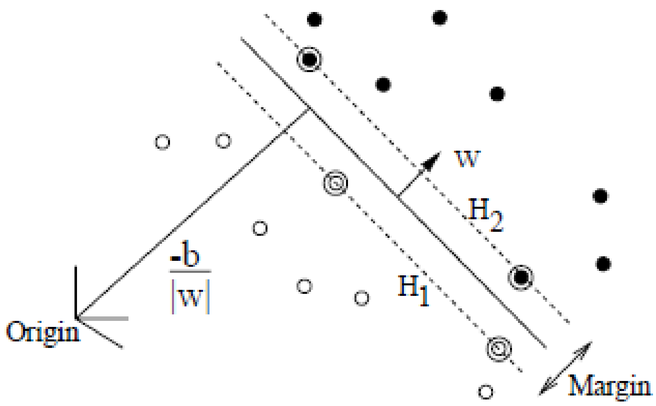


Figure 3-7: Example of linear hyperplane [118]

A hyperplane which is calculated from a training dataset $\{x_i, y_i\}$, $i = 1, 2, 3, \ldots, l$ and $y_i \in \{1, -1\}$ can be defined as $w \cdot x + b = 0$, where x is a point on the hyperplane, w is normal to the hyperplane,

b is bias and $|b|/\|w\|$ is the perpendicular distance from the hyperplane to the origin. A separate hyperplane can be defined as $w \cdot x_i + b \geq +1$ for $y_i = +1$ and $w \cdot x_i + b \leq -1$ for $y_i = -1$. The support vectors or the training points on H_1 and H_2 hyperplanes which a parallel to the OSH are defined as $w \cdot x_i + b = \pm 1$. The margin is $2/\|w\|$ and the accepted maximum margin is calculated by minimizing $\|w\|^2/2$.

In a non-separable case, slack variable ε_i is added in the constraints which become $w \cdot x_i + b \geq +1 - \varepsilon_i$ for $y_i = +1$ and $w \cdot x_i + b \leq -1 + \varepsilon_i$ for $y_i = -1$. Thus the upper bound of errors for all training data is $\sum_i \varepsilon_i$. The extra cost for errors is found by the minimized from $\frac{\|w\|^2}{2}$ to $\frac{\|w\|^2}{2} + C \sum_i \varepsilon_i$, where C is chosen by the user, higher C is a higher penalty to errors. In this study, C is sets as 1. An example of a non-separable case is shown in Figure 3.8.

For nonlinear case, the training data are mapped into high-dimensional space or Euclidean space (H) which changes the data distribution by a mapping function (φ) or $\varphi: R^d \rightarrow H$. The new data space may fit on a linear hyperplane. The input data point x is represented as $\varphi(x)$ in H. Kernel function (K) or $K(x, x_i)$ can reduced the computation of $\varphi(x) \cdot \varphi(x_i)$ in H because the training algorithm only need K instead of φ.

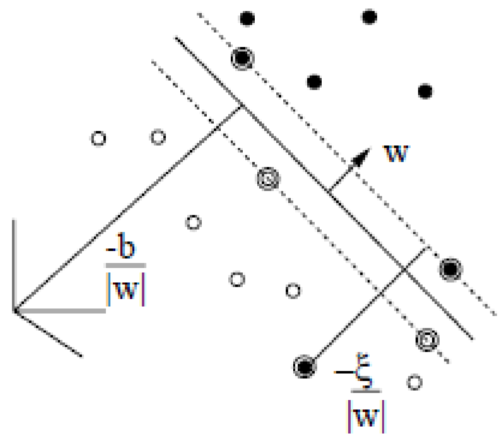


Figure 3-8: Example of the non-separable case [118]

SVMs can be applied to multi-class classification problems. There are two approaches: one-against-one (OAO) and one-against-all (OAA). The first approach creates the classification for each pair of classes. If the problem has k classes, it needs to create k(k-1)/2 classifier. Another approach compares and separates each class from the rest. If the problem has k classes, it needs to create only k classifier. In this study, OAA - SVMs are implemented by libSVM library [119].

3.2 Experiments

Five experiments were conducted on the gait representation discussed in Section 3.1.2 for the purpose of gait recognition. The first experiment was a classifier comparison between SVM and NN. The second experiment worked on the comparison of the eleven camera view angles in CASIA dataset B. The third experiment was view angle classification which recognized the view angle of probe samples. The fourth experiment took the different appearance into account in training (normal walking, wearing a coat, and with bags). The combined different appearances selected one sample per appearance per person e.g. normal walking plus wearing a coat or mixed three appearances, also tested in this experiments. The fifth experiment changes the number of training samples which are normal walking appearance.

3.2.1 Different Classifiers

SVM and Nearest Neighbor which are two common classifiers were chosen for classifier comparison testing. GEI and dimensionality reduced GEI are used in this experiment. The dimensionality-reduced GEI refers to gait features generated by the PCA from the original GEI representation. This experiment used one normal walking dataset as gallery data for training and the remaining datasets as probe data for testing. In the training process, each personal gait model was randomly trained by one-against-all SVM. This made personal gait model change at each time. Hence, all experiments in this Chapter had been trained and tested five times to find the average results. Results are shown in Table 3.1. The highlighted color is the highest correct classification rate (CCR) in each condition (Yellow-Normal walking, Blue-Carrying a bag, Pink-Wearing a coat, Orange-Mixed appearances and Green-Average three appearances and eleven view angles).

From the results, both classifiers had a better average CCR with reduced GEI data by PCA than the full GEI data. Both gait features did not have significantly different classification rate (less than 1%), nonetheless, they had much difference in a number of gait feature for each input image. In this experiment, GEI size 128x88 pixels was used as gait representation. SVM had better overall performance than NN. Even NN had slightly higher classification rate with normal walking predicting, however, SVM had much better classification result in the case of walking with bag or coat. Especially walking with coat appearance, SVM average classification rate was 15.87% (or 47.53% - 31.66%) and 15.94% (or 48.62% - 32.68%) higher than NN.

In general, both classifiers have a high classification rate when normal walking testing because the training and testing set have very a similar appearance. When walking with a bag, the classification rate was higher at 0° and 180° in which silhouette shapes have less change when compared with those at other view angles. Some person silhouette shapes are similar between normal walking and walking with a bag in some view angles due to bag silhouette overlapped to the human silhouette. Classification rate for walking with a coat has the worst performance because almost all coat appearance in this dataset had an effect on the shape of silhouette image between neck and waist, as shown in Figure 3.3.

When taking view angles into consideration with the original GEI gait representation, SVM had an explicitly higher average classification rate in all view angles. Even NN classification rate achieved over 98% at view angles of 72°, 90°, 126°, 162° and 180° with the normal walking appearance training and testing. However, NN had a lower classification rate with different appearance testing, especially at 0°, 162° and 180° for wearing coat appearance and 54°, 72° and 126° for carrying bag appearance. While SVM classification rates were between 94-96% in the normal walking testing. SVM performed better in carrying bag and wearing coat testing, especially at view angles 0° and 180° for carrying bag appearance and 18°, 36°, 54° and 90° for wearing coat appearance. The best average classification rate of NN and SVM were 65.52 and 70.53, respectively.

Table 3-1: Gait correct classification rate (CCR) (%) with different classifiers

(a) Nearest Neighbor (NN)

View Angle	Gait Energy Image as Gait Feature				Feature Extraction with PCA			
	Normal	Bag	Coat	Mixed	Normal	Bag	Coat	Mixed
0	94.83	60.34	21.55	58.91	96.55	62.07	19.83	59.48
18	94.83	57.76	31.90	61.49	95.69	60.34	33.62	63.22
36	95.69	54.31	33.62	61.21	95.69	53.45	35.34	61.49
54	97.41	45.69	38.79	60.63	96.55	43.97	37.07	59.20
72	**98.28**	44.83	35.34	59.48	97.41	43.97	37.93	59.77
90	**98.28**	51.72	35.34	61.78	97.41	52.59	**37.93**	62.64
108	97.41	54.31	31.03	60.92	97.41	54.31	34.48	62.07
126	**98.28**	45.69	33.62	59.20	**98.28**	45.69	33.62	59.20
144	97.41	50.86	31.90	60.06	96.55	50.86	33.62	60.34
162	**98.28**	56.03	27.59	60.63	**98.28**	55.17	28.45	60.63
180	**98.28**	**70.69**	27.59	**65.52**	**98.28**	69.83	27.59	65.23
Average	97.18	53.84	31.66	60.89	97.10	53.84	32.68	**61.21**

(b) Support Vector Machine (SVM)

View Angle	Gait Energy Image as Gait Feature				Feature Extraction with PCA			
	Normal	Bag	Coat	Mixed	Normal	Bag	Coat	Mixed
0	94.31	69.22	46.38	69.97	95.52	70.17	43.36	69.68
18	94.62	64.74	52.24	70.53	95.31	67.59	52.41	**71.77**
36	95.59	57.50	52.41	68.50	95.41	57.41	53.79	68.87
54	96.55	54.83	53.36	68.25	96.55	53.19	**56.12**	68.62
72	95.59	55.34	49.14	66.69	95.00	55.60	52.84	67.82
90	94.97	58.88	52.41	68.75	95.00	58.28	55.26	69.51
108	94.79	59.48	46.55	66.94	95.07	60.34	51.81	69.07
126	94.93	55.95	44.14	65.01	94.83	57.16	45.34	65.78
144	95.17	58.02	42.07	65.09	95.31	60.34	43.36	66.34
162	95.79	62.41	44.14	67.45	96.00	64.05	42.24	67.43
180	96.76	71.03	40.00	69.26	**97.21**	**72.84**	38.28	69.44
Average	95.37	60.67	47.53	67.86	95.56	61.54	48.62	**68.58**

In the case of reduced gait features by PCA, although classification rates slightly changed, almost all results had the same pattern as for the full set of GEI. The number of the full set of gait features was 11,264, whilst the reduced GEI set of data only had 116 gait feature values after PCA processing. It reduces the computation time in the further SVM training and predicting processes.

As conclusions are based on the results in the above experiments, the reduced gait representation is used as the gait features and SVM is chosen as the main classifier in this study.

3.2.2 Impact of different View Angles to gait recognition

CASIA dataset B contains gait videos in eleven view angles. With regards to an unknown gait image, first of all, view angles should be identified. Next, the view identified sample is used for personal recognition. Some research focused on the personal recognition from an identical view and some research only focused on view classification. And many gait databases capture gait video on lateral view and they do not have different view variation.

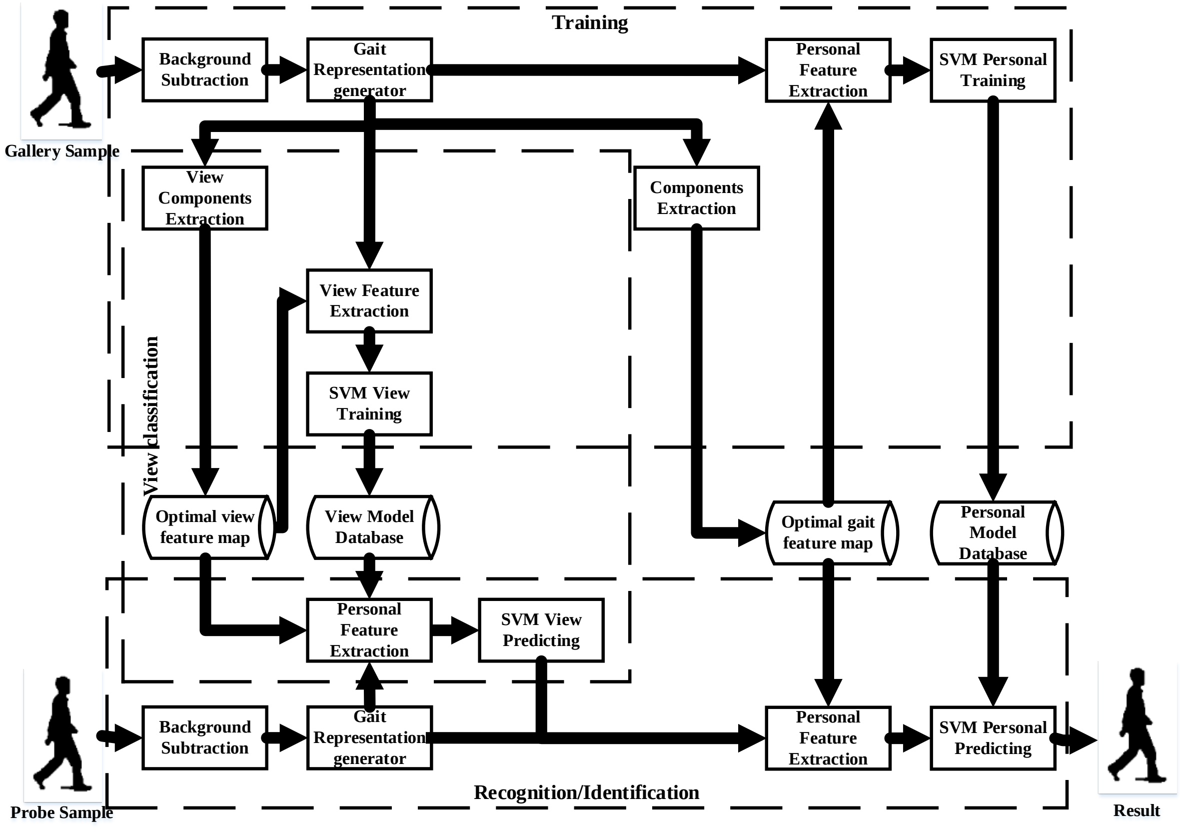


Figure 3-9: Two-step gait recognition for CASIA dataset B

Two steps gait recognition which the first step is a view angle classification and the second step is a personal recognition is constructed as it can be seen in Figure 3.9. The classification rate depends on the accuracy of both steps. Both steps are separately studied. This Chapter focused on investigating appearance changes rather than view angle classification. Personal recognition experiments in this Chapter are under identical view condition or ideal case where the view classification is assumed as 100% correct classification. Thus all view classification processes can be bypassed. The gait recognition system for personal recognition which training and testing are conducted at the same view angle is shown in Figure 3.2. After this section, gait recognition system is referred to gait recognition system by the identical view. While view classification is referred to view angle classification for unknown probe sample.

Table 3-2: Gait correct classification rate in different view angles
(N-Normal walking, B-Carrying a bag and C-Wearing a coat)

Gait Image	Condi-tion	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	AVG
GEI	N	94.31	94.62	95.59	96.55	95.59	**94.97**	94.79	94.93	**95.17**	95.79	96.76	**95.37**
	B	69.22	64.74	57.50	54.83	55.34	58.88	59.48	55.95	58.02	62.41	71.03	60.67
	C	46.38	52.24	52.41	53.36	49.14	52.41	46.55	44.14	42.07	44.14	40.00	47.53
	Mixed	69.97	70.53	68.50	68.25	66.69	68.75	66.94	65.01	65.09	67.45	69.26	67.86
GEnI	N	92.31	93.86	**95.76**	**97.21**	**96.59**	94.83	**95.28**	**95.48**	95.10	94.90	93.62	94.99
	B	**71.55**	**72.59**	**66.98**	**60.52**	**63.88**	**67.07**	**67.76**	**65.00**	**68.10**	**75.52**	**75.00**	**68.54**
	C	**54.66**	**60.69**	**60.09**	**57.67**	**52.24**	**47.67**	**45.52**	**46.98**	**46.47**	**48.88**	**41.47**	**51.12**
	Mixed	**72.84**	**75.71**	**74.28**	**71.80**	**70.90**	**69.86**	**69.52**	**69.16**	**69.89**	**73.10**	**70.03**	**71.55**
GGI	N	97.69	**96.07**	94.14	95.10	94.07	93.59	92.00	93.00	94.59	95.69	**98.28**	94.93
	B	52.07	49.74	37.33	36.03	29.14	31.12	29.05	29.83	34.05	45.00	54.66	38.91
	C	17.67	21.64	25.09	23.62	20.69	23.10	17.67	17.41	16.98	19.91	21.21	20.45
	Mixed	55.81	55.82	52.18	51.59	47.97	49.27	46.24	46.75	48.54	53.53	58.05	51.43
GGEnI	N	**98.17**	**96.07**	94.55	93.97	93.21	93.48	92.07	93.34	93.45	**96.00**	97.59	94.72
	B	59.74	56.38	44.22	40.52	38.02	38.36	37.59	41.98	44.31	51.29	60.78	46.65
	C	25.00	20.09	25.09	24.40	25.00	24.14	21.29	19.74	16.64	19.22	29.74	22.76
	Mixed	60.97	57.51	54.62	52.96	52.07	51.99	50.32	51.69	51.47	55.51	62.70	54.71

From this experiment onward in this Chapter, four gait representations, including GEI, GEnI, GGI and GGEnI, are used for training and testing in the gait identification system shown in Figure 3.2. One normal walking image sequence of each person is used to train a personal model and all the rest datasets are used as probe datasets. Results from each appearance were averaged into one classification rate at each view angle. For instance, five normal walking datasets were tested with the trained model by SVM and the CCR at 0° camera view angle was 94.31% for GEI, as shown in Table 3.2. The results of this experiment are shown in Table 3.2 and Figure 3.10.

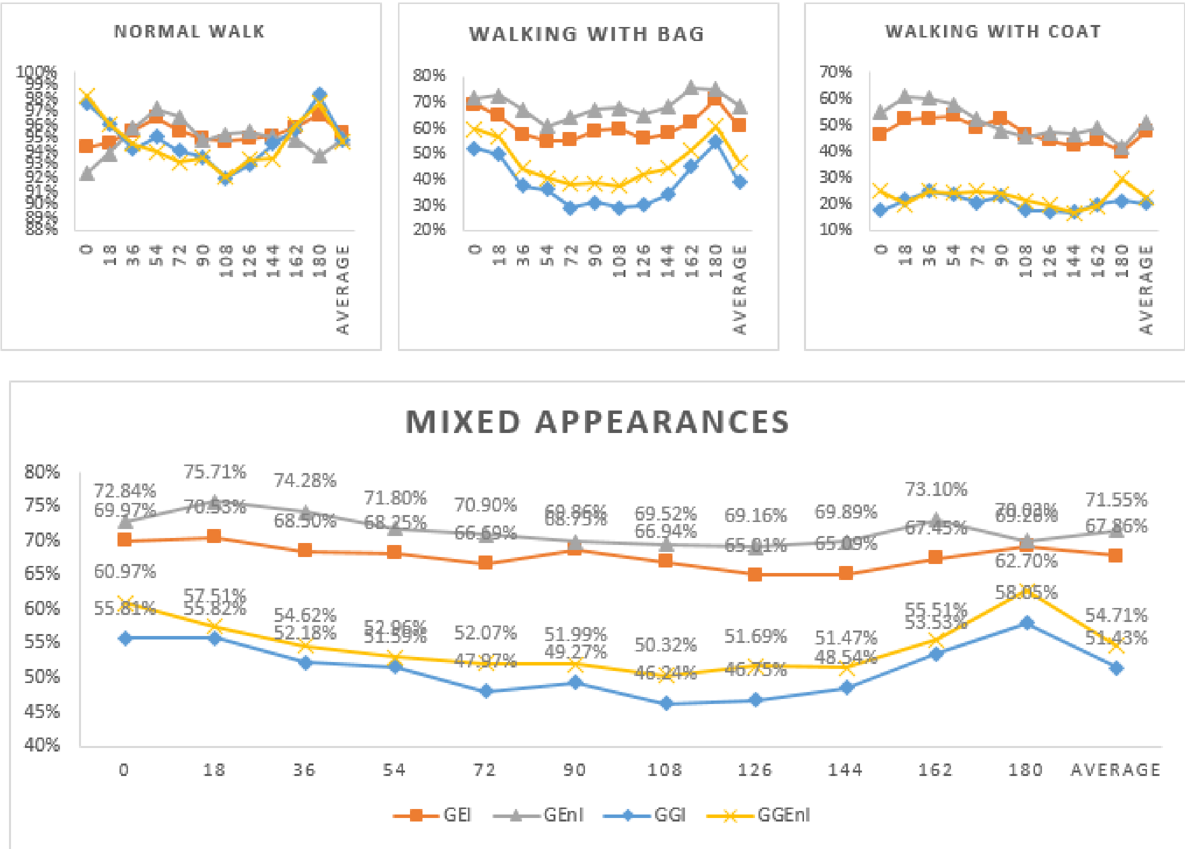


Figure 3-10: Accuracy Rate Comparison with one normal walking training dataset

In Table 3.2, GEI and GGI are considered as the original gait presentations, and GEnI and GGEnI are the derived gait representations by the entropy technique. The derived gait representation had slightly better classification rate than original gait representation. GEI and GEnI which are based on the averaging technique had a better classification rate than GGI and GGEnI. This indicates that averaged gait representations were more tolerant of appearance changes. Thus GEI and GEnI had higher than 20% when they were compared with GGI and GGEnI in case of walking with bag and walking with coat testing. Nonetheless, all representations showed relatively low classification rate with appearance changes classification rate when they were tested with wearing a coat and carrying a bag dataset.

GEnI gave the best average classification rate of 71.55% in case of mixed appearances testing because this representation had better performance with carrying bag and wearing coat appearances. The second best was from GEI which performed the best with normal walking. GGI and GGEnI had very low classification rate in the tests of carrying bag and wearing coat appearances, nonetheless, both representations achieved the rate higher than 95% with normal walking in 0°, 18°, 162° and 180°.

When each appearance is separately considered, GEI is the best representation which achieves the classification rate of 95.37% in the normal walking testing. However, GGI had the best CCR of 98.28% at view angle 180° and GGEnI had the second best classification rate of 98.17% at 0°. Both representations had lower classification rate when the camera view angle is close to 90°. In remaining appearances, GEnI had the best identification with bag and coat appearance changes at 68.54% and 51.12%. In more details, GEnI had the best classification rate for carrying bag appearance in all view angles. GEnI also had the best classification rate for wearing coat appearance in most view angles except 90° and 108° at which GEI had better classification rate.

When each view angle is separately considered, GEnI had the best classification rate of 75.71% with mixed appearances testing at view angle 18°. GEnI also performed the best with bag and coat at view angle 18° as the classification rate of 72.52% and 60.69%, respectively. The camera view angle of 180° had the best classification rate of 65.01% when taking all appearances and representations in the calculation.

On the other hand, GEnI and GGEnI which were derived from GEI and GGI, respectively, by the entropy technique had better tolerance to appearance changes when compared with the original representations. When training and testing with the normal walking dataset, the classification rate had similar values between original representation and entropy representation. Although this technique is expected to increase the classification rate when training and testing with different appearance datasets, it does not show a significant advantage in this experiment to the original representation. For example GGEnI had a better overall classification rate than GGI (3.28%), nevertheless, GEI still had a better classification rate than GGEnI had. In conclusion, the entropy technique is capable of increasing the classification rate from the original gait representation. GEnI has a better averaged classification rate than GEI and GGEnI has better averaged classification rate than GGI as can be seen in Figure 3.10.

In summary, GEnI had the best classification rate in this experiment. The Gaussian technique worked well with the same appearance of training and testing samples. The Entropy technique increases the tolerance of algorithms to appearance changes. However, this experiment trained each personal model with only one normal walking. The next experiment investigates the effect of the number of training data on the performance of gait recognition.

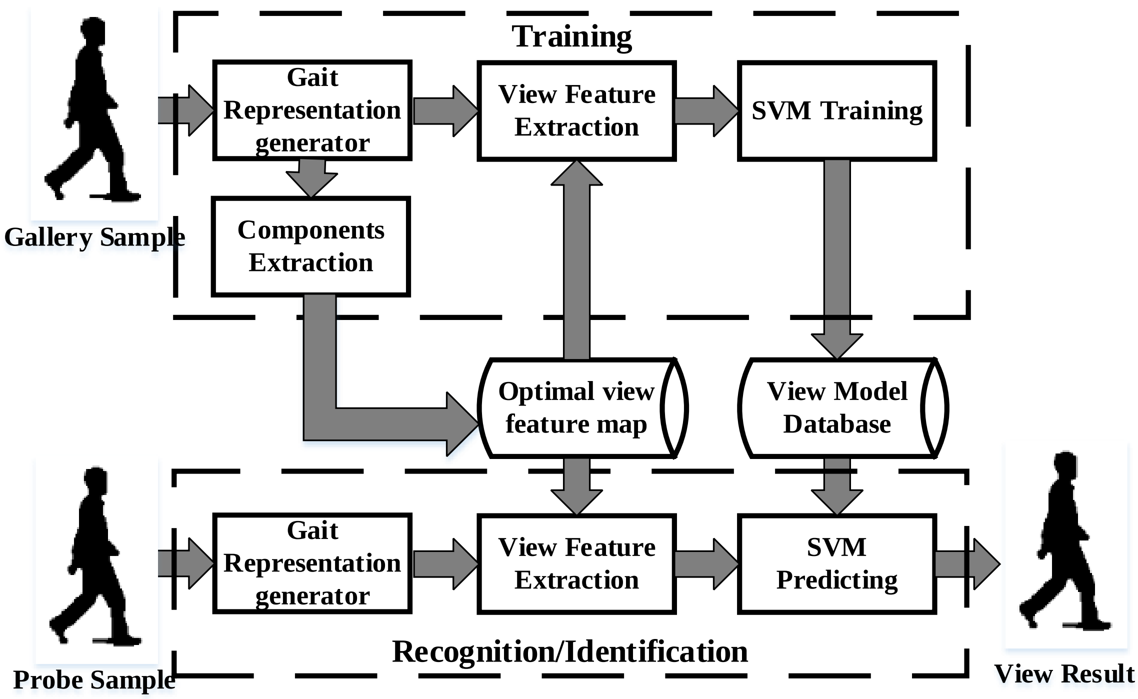


Figure 3-11: View angle classification framework

3.2.3 View Angle classification

View angle classification uses the same framework with gait recognition as can be seen in Figure 3.11. The first process is the gait representation generator which creates gait compact image from the provided image sequence. View components which are generated by PCA processes based on compact images from image sequences of all view angles are used to produce the optimal view feature map. This map is used to select features from input compact gait images. Next, the selected features are treated as the input for view model training and prediction by SVM. In testing, the input is tested with all view models and the model with the highest score is chosen as an output result.

This experiment chose the four normal walking datasets as the training set and the remaining datasets were used as the testing set. The optimal view feature map was created from image sequences of all view angles for the first twenty-four people in the training set (24 persons x 11 views x 4 normal walking sequences = 1,056 gait sequences). Gait representations of GEI, GEnI, GGI, and GGEnI are used in the first experiment. Results are shown in Table 3.3.

Table 3-3: View angle classification rate by basic gait representations
(N-normal walking, B-carrying a bag and C-wearing a coat)

View Angle	GEI			GEnI			GGI			GGEnI		
	N	B	C	N	B	C	N	B	C	N	B	C
0	98.3	77.6	81.0	98.7	89.2	87.5	**99.6**	84.5	90.9	**99.6**	**95.7**	**94.8**
18	99.6	80.6	93.1	99.6	86.6	92.7	**100.0**	79.7	**96.6**	**100.0**	**94.4**	96.1
36	98.3	92.7	89.2	99.1	90.1	90.9	**100.0**	95.7	**96.1**	**100.0**	**97.8**	94.4
54	98.3	78.0	82.8	97.4	85.3	85.3	**100.0**	90.1	93.5	**100.0**	**97.8**	**94.0**
72	99.6	88.8	91.8	99.1	94.8	88.8	**100.0**	88.8	**89.2**	**100.0**	**98.3**	86.2
90	97.4	57.8	67.2	98.7	59.1	66.8	99.1	68.5	65.9	**100.0**	**91.8**	**75.0**
108	96.6	56.0	90.1	96.6	74.6	90.5	**100.0**	68.5	**95.7**	99.6	**84.5**	91.8
126	100.0	**97.8**	91.4	100.0	97.4	83.2	**100.0**	94.8	92.2	**100.0**	97.4	**96.6**
144	98.3	80.6	**87.9**	98.3	82.3	76.7	**99.1**	**87.9**	92.7	**99.1**	**90.5**	85.8
162	99.1	72.8	90.1	99.1	84.5	92.2	**99.1**	87.1	94.0	**99.1**	**95.3**	**94.4**
180	99.1	88.8	85.8	99.1	**92.2**	90.5	**99.6**	83.6	93.1	99.1	**92.2**	**94.8**
Means	98.6	79.2	86.4	98.7	85.1	85.9	**99.7**	84.5	90.9	**99.7**	**94.2**	**91.3**
	88.07%			89.92%			91.69%			**95.04%**		

From the results in Table 3.3, a view angle which had the lowest classification rate was 90°. If all appearances test had been averaged, the view angles which had the highest classification rate were 126°-GEI, 72°-GEnI, 36°-GGI and 126°-GGEnI. A Gaussian technique which was calculated the relationship of all pixel in the same position from complete gait cycle sequence images had the better view angle classification rate than average techniques or GEI and GEnI, while the entropy technique which removed unnecessary (unmoved) information slightly increased the view angle classification rate. Finally, GGEnI which was generated from both Gaussian and entropy techniques has the highest mean classification rate of 95.04%.

3.2.4 Number of training datasets

This experiment controls the number of training samples. Normal walking appearance is chosen as the gallery set because this appearance was captured six times per person. In the first experiment, the number of training samples was increased from one to four. At the same time, gait features were also compared between a full-size gait representation image and reduced/selected features by PCA. In this testing, gait representation size was 128x88/11,264 pixels, while the number of features for the reduced data size was fixed at 116. The average results from all view angles are shown in Table 3.4.

Table 3-4: Different Gait Representations with different numbers of training datasets

Gait Representation	Appearances	Gait Representation Image				Reduced data by PCA			
		Number of Training Dataset				Number of Training Dataset			
		1	2	3	4	1	2	3	4
GEI	Normal	**95.37**	98.68	**99.21**	99.14	**95.56**	98.70	**99.15**	**99.15**
	Bag	60.67	68.85	69.95	71.82	61.54	67.63	67.61	69.94
	Coat	47.53	54.59	54.62	55.24	48.62	53.20	53.98	54.79
	Mixed	67.86	74.04	74.59	75.40	68.58	73.18	73.58	74.63
GEnI	Normal	94.99	**98.74**	99.02	**99.15**	95.12	**98.72**	98.87	99.07
	Bag	**68.54**	**76.49**	**78.07**	**80.81**	**68.47**	**75.67**	**76.67**	**78.54**
	Coat	**51.12**	**57.78**	**57.30**	**60.17**	**50.42**	**56.83**	**55.55**	**58.35**
	Mixed	**71.55**	**77.67**	**78.13**	**80.04**	**71.33**	**77.08**	**77.03**	**78.65**
GGI	Normal	94.93	98.13	98.78	99.09	94.88	98.15	98.61	99.04
	Bag	38.91	43.92	46.67	48.23	38.17	42.58	45.10	46.68
	Coat	20.45	26.61	28.72	29.75	20.47	26.12	27.34	29.11
	Mixed	51.43	56.22	58.06	59.02	51.18	55.62	57.01	58.28
GGEnI	Normal	94.72	98.11	98.65	98.99	94.91	98.05	98.55	98.88
	Bag	46.65	54.71	57.33	58.61	46.54	52.90	54.85	57.11
	Coat	22.76	28.96	31.51	32.40	22.35	27.93	29.82	30.99
	Mixed	54.71	60.59	62.50	63.33	54.60	59.63	61.07	62.32

From the results presented in Table 3.4, the reduced data by PCA achieved the similar classification rate as the full data gait representation image did. The same as Table 3.1, reduced gait feature by PCA had very similar classification rate with gait representation. The average technique had better performance than the Gaussian technique. The Entropy technique had increased appearance change tolerance with the wearing coat appearance still having the lowest classification rate. This is shown by the result in Table 3.4. GEnI had the highest classification rate followed by GEI, GGEnI and GGI. When the number of training samples increased, the classification rate was increased as well. Especially from one training sample to two training samples, the identification rate is increased by about 5%. The experimental results suggested (1) using at least two training samples for each person in practice, and (2) the reduced features (116 features for each person) by PCA work as well as the full set of gait representation in gait identification.

Table 3-5: Different number of training datasets

Gait Representation	Appearances	Number of the training set					
		1	2	3	4	5	6
GEI	Normal	**95.56**	98.56	**99.18**	99.14	**100.00**	**100.00**
	Bag	61.54	68.67	69.67	71.69	73.33	73.12
	Coat	48.62	54.66	55.00	55.44	55.73	55.63
	Mixed	68.58	73.96	74.62	75.42	76.35	76.25
GEnI	Normal	95.12	**98.67**	99.00	**99.15**	**100.00**	**100.00**
	Bag	**68.47**	**76.47**	**77.93**	**80.81**	**81.18**	**81.46**
	Coat	**50.42**	**58.41**	**57.71**	**60.05**	**59.28**	**60.49**
	Mixed	**71.33**	**77.85**	**78.21**	**80.00**	**80.15**	**80.65**
GGI	Normal	94.88	98.26	98.73	99.08	99.47	**100.00**
	Bag	38.17	43.50	46.71	47.98	48.49	48.95
	Coat	20.47	26.82	29.18	29.81	31.15	31.61
	Mixed	51.18	56.19	58.21	58.96	59.70	60.19
GGEnI	Normal	94.91	98.11	98.66	98.94	99.50	**100.00**
	Bag	46.54	54.27	57.53	58.72	59.89	60.26
	Coat	22.35	29.26	31.45	32.47	34.02	34.58
	Mixed	54.60	60.55	62.55	63.38	64.47	64.95

The experiment was conducted by increasing the number of gait features from the PCA process by which the selected features could be up to the number of training objects. Thus the maximum number of reduced data is equal to the number of training datasets multiplying the number of video sequences in each dataset. In this case, each dataset had 116 people, so the maximum number of two, three and four training datasets were 232, 348 and 464, respectively. In this experiment, the number of training datasets increased from one to six because there are six normal walking datasets in CASIA dataset B. When all six normal walking datasets were used to the training phase, the same six normal walking was used in testing phase as well. This means both the training and testing phase used the same normal walking dataset. The average results are shown in Table 3.5.

The classification rate in Table 3.5 slightly increased compared with those in Table 3.3. From the results, it can be seen that six training datasets produce a better classification rate. Nonetheless, in this circumstance, the normal walking testing sample was the same with training samples. By using five training samples per each person, the classification rate for normal walking appearance was 100%. All appearances were completely different between the training and testing dataset. Results for four training datasets in each view angle are demonstrated in Figure 3.12. The classification rate clearly increased when compared with those in Figure 3.9. Interestingly, the profiles in Figures 3.10 and 3.12 are similar. All experiments conducted in Section 3.4.1, 3.4.2 and this section use only normal walking training dataset. In the next section, the investigation is focused on training a personal model by different appearance training datasets

Figure 3-12: Accuracy Rate Comparison with four normal walking training dataset

3.2.5 Training samples including various appearances

In the previous experiments, only normal walking datasets are involved in training. This experiment changed training sets from only normal walking appearance to walking with a bag, wearing a coat and combination of appearances. The number of reduced gait features depends on the number of training sets, for example only carrying bag appearance is used as the training set, and only one training set, thus the reduced data has 116 features; in the mixed appearance training, one training set from each appearance for each person, there are three sample gait representation images thus the reduced dataset has 348 or 3*116 features. The average classification rate is presented in Table 3.6.

When training personal models with different single appearances, the averaged classification rate of normal walking training was highest compared with the other appearance training. Wearing a coat and with bags could change the silhouette shape from the normal walking gait representation. In this dataset, it is noticed that the position of the bag introduced more variety than wearing a coat does. When training and testing personal models with the same appearance. Wearing a coat has the highest classification rate of 98.32% GEnI while carrying a bag has the highest classification rate of 93.34% GEnI.

In the case of mixed two appearances in training, i.e. normal walking and walking with bag combination, GEI and GEnI averaged classification rate was more than 81%. While the Gaussian technique still had a problem with appearance change. The GGI and GGEnI best averaged classification rates were 61.86% and 65.55%. Finally, all appearances were mixed together in the training process. It produced the high classification rate in all test cases. When personal models were trained by using two or three appearances, these models had the better overall classification rate. Especially the average classification rate from the Gaussian technique which makes use of neighbour pixels in gait representation images was increased dramatically up to 20%. However, compared with the results from the training/testing with the same single appearance, the classification rate with some representation has dropped especially GGI and GGEnI. For example, GGI has achieved the classification rate of 87.35% in the case of both training and testing by using walking with a bag, whilst the best classification rate was only 82.18% for walking with bag testing when the model was trained by two or three appearances.

The average technique also had better average results over the Gaussian technique. In a combination of appearance training, the classification rate produced by the average technique was not obviously dropped when compared with those from the same single appearance training and testing. Especially, walking with bag appearance had better results in many cases. For example, GEI achieved the classification rate of 91.88% when both training and testing by walking with a bag. The best walking with bag classification rate was 95.22% when all appearances were involved in training. Last but not the least, GEI had beaten GEnI in case of mixed appearances which had adequate information for all three appearances in CASIA dataset B.

Table 3-6: Different appearances training dataset

Gait Representation	Appearances	Training Set						
		Normal	Bag	Coat	Normal/Bag	Normal/Coat	Bag/Coat	Mixed
GEI	Normal	**95.56**	57.76	42.89	92.89	90.04	67.39	**95.25**
	Bag	61.54	91.88	35.27	93.10	67.32	86.08	95.22
	Coat	48.62	35.50	98.26	57.74	**95.03**	91.00	**98.39**
	Mixed	68.58	61.72	58.81	81.25	84.13	81.49	**96.29**
GEnI	Normal	95.12	**64.12**	**45.24**	**94.22**	**90.26**	**71.68**	94.77
	Bag	**68.47**	**93.34**	**43.05**	**94.36**	**72.48**	**86.74**	**95.67**
	Coat	**50.42**	**42.01**	**98.32**	**61.57**	94.78	**91.36**	97.96
	Mixed	**71.33**	**66.49**	**62.20**	**83.38**	**85.84**	**83.26**	96.14
GGI	Normal	94.88	42.30	23.59	82.13	69.95	39.60	86.28
	Bag	38.17	87.35	14.76	80.33	33.50	62.68	82.18
	Coat	20.47	13.43	96.72	23.11	73.81	66.90	86.85
	Mixed	51.18	47.69	45.03	61.86	59.09	56.39	85.10
GGEnI	Normal	94.91	45.53	26.24	85.81	72.63	44.48	88.24
	Bag	46.54	87.41	18.97	83.04	41.41	65.85	84.39
	Coat	22.35	16.54	96.85	27.79	74.78	70.63	89.48
	Mixed	54.60	49.83	47.35	65.55	62.94	60.32	87.37

3.3 Summary

This Chapter has presented four different gait compact images, GEI, GEnI, GGI and GGEnI as gait representations. In the first experiment, it has been noticed that although the NN classifier achieved better gait classification rate in the case of the same appearance used in training and testing, SVMs performed better in overall average accuracy than NN. Reduced GEI data by PCA worked well in gait identification as classification rate the full original GEI data were used as features in classification.

In the second experiment, the best view angle for each gait representation was different. The 90° view angle which shows the most detail of gait action had almost the same classification rate with an average classification rate from every view angles. When only using normal walking in training, the classification rate testing walking with coat appearance is very low in every view angle.

In the third experiment, the view angle classification is explored. The Gaussian technique is more suitable than the average technique for all appearances as it can be seen from GEI and GGI classification results in Table 3.3. Gaussian technique calculates each pixel value with the relationship variable from all pixels in the same position from gait cycle frames. While GEI and GEnI are directly generated from the average value from gait cycle frames. This makes a Gaussian image is more suitable for represented one specific information but it does not suitable for the covariate condition. In the other way, the entropy technique which removes the unnecessary information by comparing the pixel value with their neighbour pixels can improve the mean classification rate as it can be seen from the comparison GEI with GEnI and GGI with GGEnI. In almost all cases GEnI and GGEnI give the better classification rate that GEI and GGI except for GEI walking with a coat and GGI normal walking. Especially, the classification rate of walking with bag appearance has increased by approximately 5% in the case of GEnI and 10% in the case of GGEnI. The view angle of 90° has very low classification rate when this view is tested by walking with a coat and carrying a bag datasets.

In forth experiments, observations were drawn that the number of training samples does affect gait classification rate. When changing the training samples from one to two with normal walking only, the classification rate increased 5%. In the case of normal walking testing, GEI and GEnI have 100% classification rate when personal models are trained by five normal walking samples per person.

The last experiment has shown that normal walking appearance tends to achieve better classification rate than walking with a bag or wearing a coat appearance. Nevertheless, walking with a coat had the best classification rate with the same appearance in training and testing. When the number of different appearance samples was increased in the training phase, the average classification rate increased. However, the classification rate of the same appearance testing slightly decreased especially in the case of GGI and GGEnI.

In this Chapter, full representation image and reduced dimension data by PCA have a similar classification rate when both of them are used to train and test personal model by SVM and NN. SVM has a better classification rate than NN. GEnI has the best classification rate following GEI except for mixed three appearance training in Table 3.5. GGEnI had better average classification rates than GGI. All representation have appearance change problems. In the next Chapter, Convolutional and Histogram of Orientation Gradients techniques are introduced to generate the secondary gait representation which use the four representations in this Chapter as basic representation. These representations work with PCA and SVMs as the same with this Chapter.

Chapter 4 Extensive Development of Gait Representations

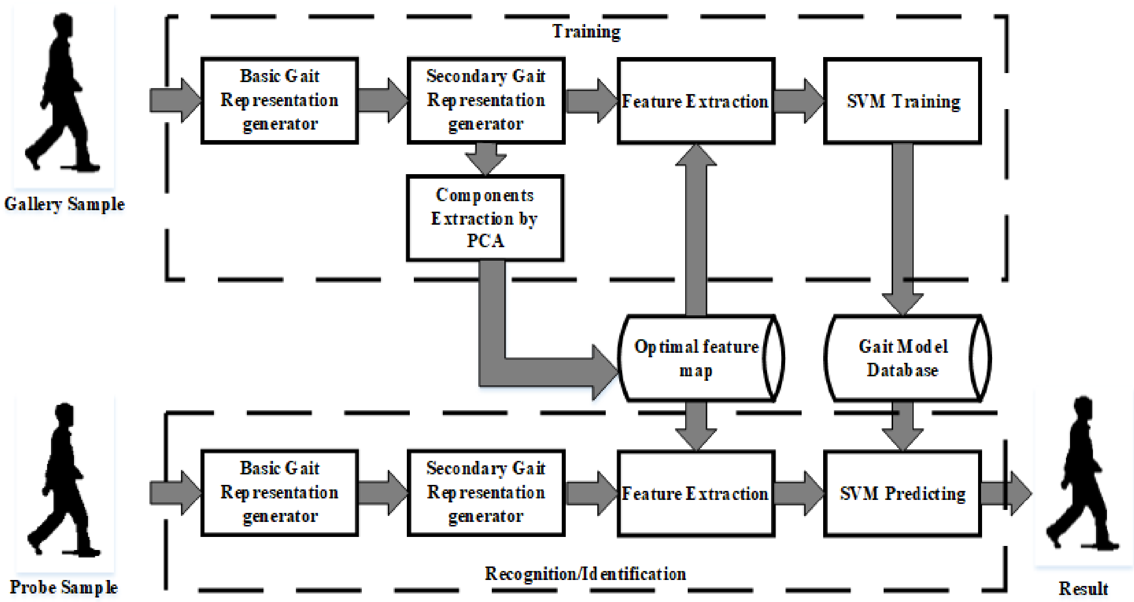
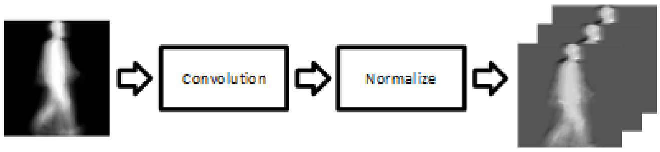


Figure 4-1: General Gait Recognition Framework

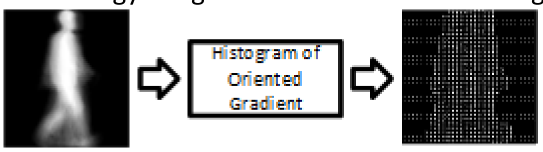
Chapter 3 presented the gait recognition framework which has four main processes, gait representation generation, feature extraction or data reduction by PCA, SVM training, and SVM prediction. Four gait representations, GEI, GEnI, GGi and GGEnI, are tested on CASIA dataset B based on the framework. In this Chapter, all previous gait representations are used as a basic representation for generating three other kinds of new gait representations or secondary gait representations as it can be seen in Figure 4.1. The first representation is called Convolutional Gait Image (CGI) which is obtained by applying convolutional operations to a basic gait representation. The second representation is called Gradient Histogram Gait Image (GHGI) which is generated by the Histogram of Oriented Gradients (HOG) operations on a basic gait representation. The third new representation is called Convolutional Gradient Histogram Gait Image (CGHGI), obtained by applying convolutional operations and histogram of oriented gradients techniques to a basic gait representation. Examples of three new gait representations are shown in Figure 4.2. The rest of this Chapter is divided into five sections. The divisions are as follows, three sections on the new kinds of gait representations, CGI, GHGI and CGHGI followed by the view angle classification and a concluding summary.

4.1 Convolutional Gait Image (CGI)

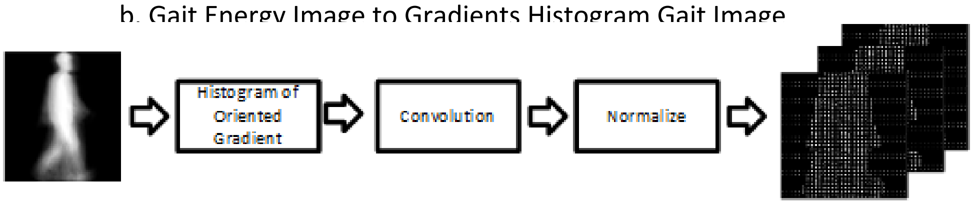
The idea of CGI development is from Convolutional Neural Network (CNN), nonetheless, the convolutional technique is only used to generate a gait representation. CNN architecture is created from the combination of computation block or computational layers which include convolutional, normalized, pooling, rectified linear unit (ReLU), fully connected and loss layer[120]. The complexity of CNN depends on different layer combinations and the number of hidden layers. However, CGI discards the complexity of neural network and uses only a single convolutional and normalization block. Both CGI computational block implements following the MatConvNet computation blocks which is a MATLAB implementational CNN[120]. This gait representation uses each calculating block only one time. This section contains three parts, the detail of computation blocks, preliminary experiment, CGI experiment and discussion.



a. Gait Energy Image to Convolutional Gait Image



b. Gait Energy Image to Gradients Histogram Gait Image



c. Gait Energy Image to Convolutional Gradient Histogram Gait Image

Figure 4-2: Gait representation processes

4.1.1 Computational Blocks

The new gait representation which is the convolved images is generated from the original gait representation (GEI) by convolutional block and batch normalization block as can be seen in Figure

4.2(a). Computational blocks use the same computational blocks in MatConvNet thus all methods for CGI are the same as MATCONVNET computational blocks. All CGI and CGHGI experiments are implemented with MATCONVNET toolbox which is designed for MATLAB. Three MatConvNet computational blocks which are related to this study are described in following sections.

a) Convolutional Block

Convolutional block computes the convolution of the input *x* with *M* multi-dimensional filters bank and biases b. The output is formally given by

$$y_{i''j''d''} = b_{d''} + \sum_{i'=1}^{H'} \sum_{j'=1}^{W'} \sum_{d'=1}^{D} f_{i'j'd} \times x_{i''+i'-1,j''+j'-1,d',d''} \tag{4.1}$$

where $x \in R^{H \times W \times D}$, $f \in R^{H' \times W' \times D \times D''}$ $y \in R^{H'' \times W'' \times D''}$, b is bias, H is height, W is width and D is depth or the number of images In stack.

The fully connected layer in MATCONVNET has the same function as the convolutional block, however, its output y has dimensions $H'' = W'' = 1$.

b) Pooling Block

The main purpose of this block is data reduction. MatConvNet has two pooling operations, these include max and sum pooling. The pooling block in this study reduces the size of input by computing the maximum response of each feature channel in a filter size $H' \times W'$.

$$y_{i''j''d} = \max_{1 \le i' \le H', 1 \le j' \le W'} x_{i''+i'-1,j''+j'-1,d} \tag{4.2}$$

In this research, pooling blocks are used to rapidly reduce the size of input data. Pooling block is a very popular block in CNN layers, however, it is intentionally not used in CGI to avoid information loss.

c) Batch Normalization Block

The batch normalization block computes across images/feature-maps in a batch, to normalize each channel of the feature map *x*. The output feature map is given by

$$y_{ijkt} = w_k \frac{x_{ijkt} - \mu_k}{\sqrt{\sigma_k^2 + \varepsilon}} + b_k \tag{4.3}$$

$$\mu_k = \frac{1}{HWT} \sum_{i=1}^{H} \sum_{j=1}^{W} \sum_{t=1}^{T} x_{ijkt} \tag{4.4}$$

$$\sigma_k^2 = \frac{1}{HWT} \sum_{i=1}^{H} \sum_{j=1}^{W} \sum_{t=1}^{T} (x_{ijkt} - \mu_k)^2 \tag{4.5}$$

where $x, y \in R^{H \times W \times K \times T}$, $w \in R^K$, $b \in R^K$ and T is the number of images in a batch. ε is a small cost which solved the divided by zero problem.

It is worth to note that this study only adapts the forward mode in CNN. There is no back propagation involved in adjusting bias parameters in (4.3) and (4.5) so that all bias parameters are set to zero. When CGI is created by combined basic computational blocks is tested, bias parameter can be set to zero or CGI is created with only forward propagation because bias parameters are less affected from the preliminary research when CGI is generated by a single layer computational block.

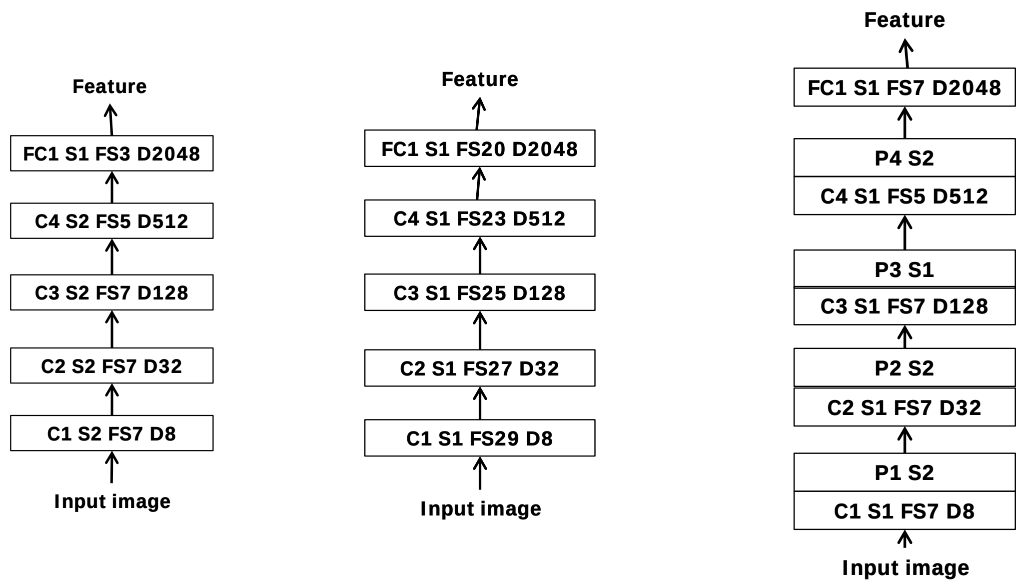
4.1.2 Preliminary experiments

Preliminary experiments are based on the combination of the computational block as it can be seen in Figure 4.3 and 4.4. All combinations are constructed the same way with CNN architecture but only forward propagation is operated. Mixed appearance datasets which include one sample from each appearance in CASIA dataset B were chosen as the training set. GEI (120x120 pixels) was selected as the input for combined blocks and the output was used as the input to SVM for training/testing.

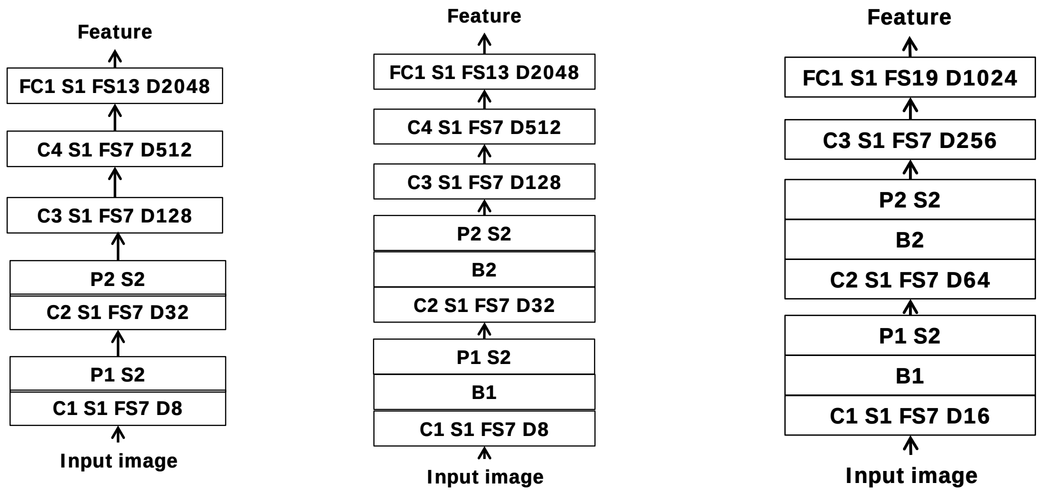
Various configurations were attempted in block selection. From Figure 4.3, each computational block may result in different extracted features so that the combination of the blocks in each layer is carefully designed for an optimal architecture. Figure 4.3 (a) shows experiment A-1, in which all layers only have a convolutional block with a small filter size but different stride size. First convolutional layer or C1 uses filter size 7x7, stride size 1 and depth 8. Second and third layer use the same setting, but the depth size is respectively increased to 32 and 128. The fourth layer uses filter size 5x5, stride size 2 and depth 512. The final layer is fully connected that all networks connected together to generate . The output from this layer is the vector size 2048 which is the same as depth. The final layer uses filter size 3x3, stride size 1 and depth 2048. Figure 4.3 (b) shows the increased filter size with the stride equal to one at all layers. For example, C3 layer uses filter size 25, stride size 1 and depth 128. Architecture (a) uses a bigger stride size to maintain a number of the convolutional blocks while architecture (b) uses the filter size to maintain a number of convolutional blocks. In Figure 4.3 (c), pooling blocks are added into the architecture and convolutional block used a small filter size with the stride size equal to one. For example, the first convolutional layer or C1 uses filter size 7x7, stride size 1 and depth 8. First pooling layer or P1 which give the same output depth as input depth uses stride size 2. This aims to investigate the effect of pooling block on the gait recognition result. Figure 4.3 (d) shows the architecture which reduces the number of pooling block and increases the filter size. The final layer must use the bigger filter size because it does not have the P3 and P4 layer as (c) has. In Figures 4.3 (e) and 4.3 (f), batch normalization blocks are added into the architecture. This kind of layer is batch normalization which normalizes across convolutional block output. The output from this block has the same size as input. The effect of normalization block and a number of layers on the recognition results are tested.

From the correct classification rate (CCR) shown in Table 4.1, the following observations are presented.

- The setting with the smaller filter size and larger stride gave higher recognition accuracy than that of the larger filter size and smaller stride with the same number of layers.



(a) Experiment A-1 (b) Experiment A-2 (c) Experiment A-3



(d) Experiment A-4 (e) Experiment A-5 (f) Experiment A-6

Figure 4-3: The configuration of computational blocks for feature extraction: C-Convolutional, S-Stride, B- Batch Normalize, P-Pooling, FC-Fully Connected layer, FS-Filter size, D-Depth

- The stride in convolutional block gave better recognition accuracy when compared to the same stride size in pooling block.
- Too many pooling blocks may decrease the recognition accuracy as it can be seen from experiments A-3 and A-4.
- Normalized data which had been computed by batch normalization block had increased the recognition accuracy.

- Enlarging filter size of the fully connected layer was equivalent to more convolutional blocks in operation. It increased the recognition accuracy as seen from experiments of A-5 and A-6. The results from these two experiments show optimal settings of a computational block in the gait recognition.

Table 4-1: Results of Various Computational Block Combinations

Experiment	Appearance			
	Normal	Bag	Coat	Average
A-1	90.56	89.89	91.82	90.76
A-2	90.83	87.84	91.72	90.13
A-3	90.77	88.65	92.08	90.50
A-4	91.33	88.93	92.15	90.80
A-5	95.41	92.93	96.14	94.83
A-6	**96.90**	**95.25**	**97.59**	**96.58**

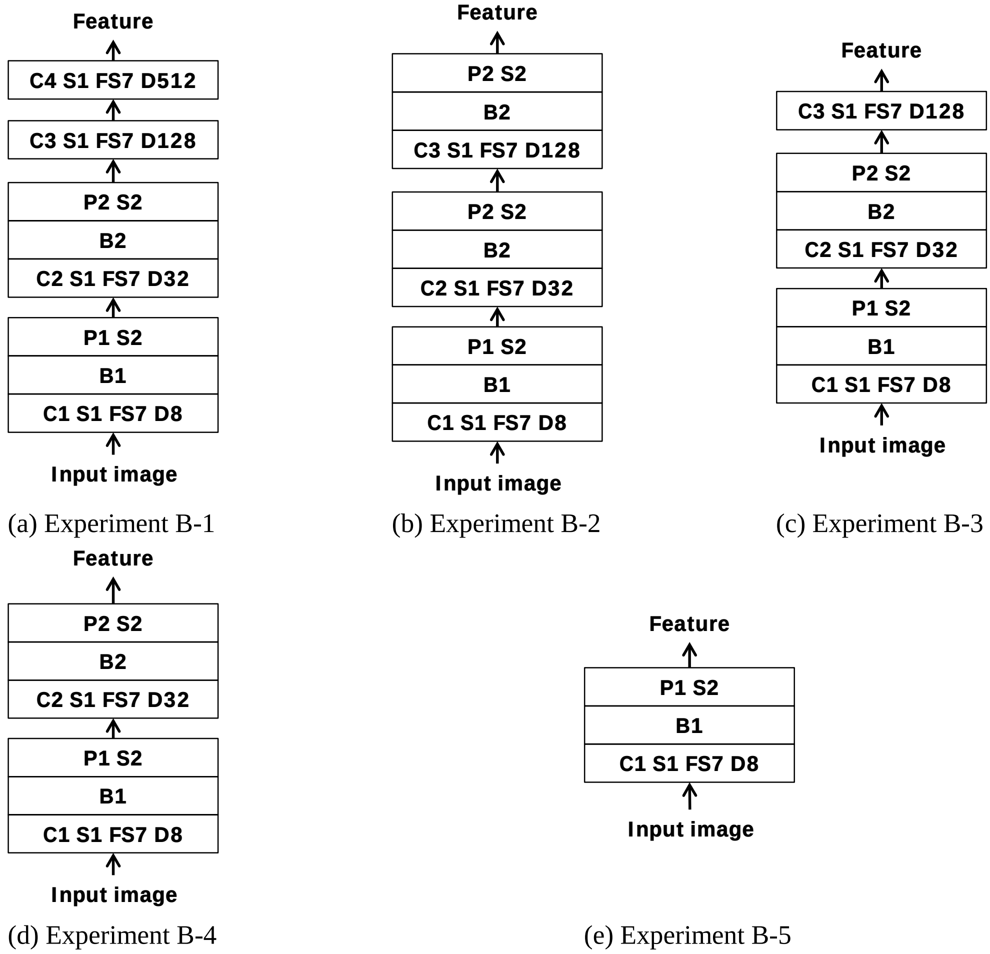


Figure 4-4: Reduced computational layers: C-Convolutional, S- Stride, B- Batch Normalize, P-Pooling, FS-Filter size, D-Depth

In a new setting as shown in Figure 4.4, the number of computational layers is reduced based on experiments A-5. The number of layers is gradually reduced from five to one with various computational blocks. The recognition accuracy of each experiment is shown in Table 4.2.

Table 4-2: The CCR of Experiment B

Experiment	Appearance			
	Normal	Bag	Coat	Average
B-1	97.13	88.78	96.94	94.28
B-2	96.76	88.73	97.45	94.31
B-3	97.23	89.51	97.90	94.88
B-4	97.45	90.63	97.87	95.31
B-5	**97.46**	**91.58**	**97.96**	**95.67**

Interestingly, it can be seen from Table 4.2 that the CCR has increased when the number of layers is reduced, especially in the case of carrying a bag appearance (showing as "Bag" in Table 4.2), in which it increased from 88.78 to 91.58. Although the recognition accuracy is lower than the result from experiment A-5 and A-6 in Table 4.1 which used features from the fully connected layer, this experiment needs less computational time for feature extraction.

Inspired by the result from Experiments A and B, it was attempted to only use one convolutional block and one batch normalization block as a feature extractor in Experiment C. These experiments investigate the effect of different kernel sizes, i.e. 3x3, 5x5, 7x7 and 9x9, on gait recognition accuracy. The results from different filter size are shown in Table 4.3. Interestingly, the best recognition accuracy rate obtained in Experiment C was better than the best result in Experiment A (96.58) and B (95.67). Normalized CGI which was generated by both convolutional and normalization block also had higher recognition accuracy rate than the other experiments. Kernel size 3x3 achieved the highest rate of 97.88 in this experiment.

Table 4-3: the CCR of single convolutional block

Filter size	Convolutional Block				Convolutional and Batch Normalization Block			
	Normal	Bag	Coat	Average	Normal	Bag	Coat	Average
3x3	96.46	94.56	97.70	96.24	97.52	**97.24**	**98.89**	**97.88**
5x5	**97.98**	**96.49**	**98.68**	**97.72**	**97.74**	96.88	98.59	97.74
7x7	95.61	94.06	97.15	95.61	97.49	96.11	98.35	97.32
9x9	96.90	95.30	98.01	96.73	97.27	95.99	98.04	97.10

4.1.3 CGI experiment: comparison of CNN and SVM classifiers in gait recognition

So far, the CNN architecture is only used for generating features in gait recognition. In this section, with back propagation, CNN is also used as a classifier and compared with SVM classifier in the gait recognition task. Based on the results from the preliminary experiments demonstrated in Section 4.1.2, the CGI experiment presented in this section was constructed with filter size 3x3. Only 3 normal walking appearance samples per person were chosen as a training set for all experiments in this section. The rest samples, three normal walks, two with bags, and two wearing coats were used for testing.

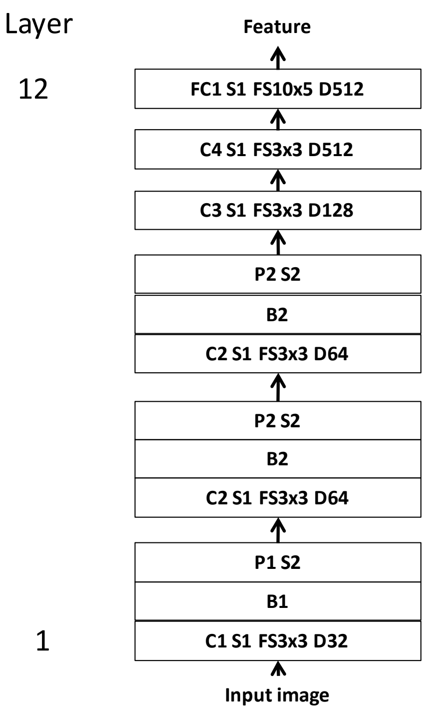


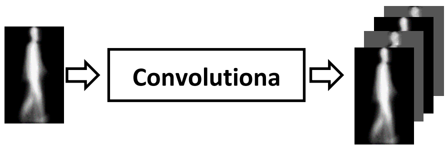
Figure 4-5: The configuration of the computational block for feature extraction: C-Convolutional, S- Stride, B- Batch Normalize, P-Pooling, FC-Fully Connected layer, FS-Filter size, D-Depth

Table 4-4: CNN and SVM correct classification rate

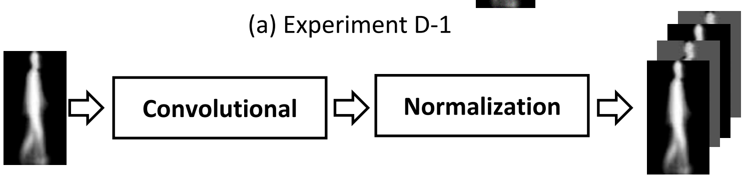
Layer	Classifier	Appearance			
		Normal	Bag	Coat	Average
12	CNN	87.07	52.16	43.53	60.92
11	SVM	98.08	49.61	29.39	59.03
10		98.63	59.68	36.76	65.02
9		99.02	72.53	47.14	72.90
8		99.06	75.94	49.10	74.70
7		98.98	73.82	46.75	73.18
6		99.06	77.04	51.33	75.81
5		**99.18**	**78.21**	52.98	**76.79**
4		98.98	74.65	48.90	74.18
3		99.06	77.08	52.70	76.28
2		99.10	77.70	53.10	76.63
1		99.10	76.61	**54.47**	76.72

The first experiment was the comparison between CNN and SVM classifier which were tested with the architecture shown in Figure 4.5. This architecture was trained by normal CNN operation which has both forward and backpropagation. The bias parameters for each layer were optimized during CNN training operation. In testing, CNN classifier was tested with the output feature from the fully connected layer as the normal CNN operation, while SVMs were tested with results from each layer which already applied bias or trained parameters. Results are shown in Table 4.4.

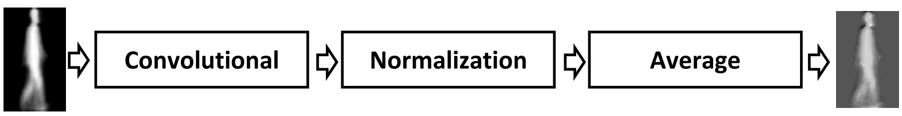
As can be seen in Table 4.4, with a reduced number of layers in the CNN architecture, the output features made SVMs slightly increase their gait recognition accuracy. This experiment result had the same pattern with previous section experiments in Table 4.2. When the number of layers was decreased, the accuracy increased. Only one convolutional and one normalization block was involved for generating gait feature. This classification rate is better than that from the original GEI in Table 3.3. SVMs performed better than CNN in this experiment. Trained parameters had less effect on classification rate because there were fewer layers architecture when compared with the CNN architecture.



(a) Experiment D-1



(b) Experiment D-2



(c) Experiment D-3

Figure 4-6: Convolutional Gait Image Experiments

4.1.4 CGI on different gait representations

From the previous experiment, convolutional and normalization blocks were considered as the main block for this study. These experiments optimize the accuracy rate of CGI which used one or two computational blocks to generate features with four input gait representations from the previous Chapter. There were three different setting as can be seen in Figure 4.6. Experiment D-1 generates gait features by a convolutional block which returns a stack of convolved images. The single convolutional block was applied with input gait representation by randomizing filter without padding. The number of outputs depended on the number of filter depth. If filter depth was three, the number of outputs in the stack was also three. The output size was much greater than the input size. Experiment D-2 added batch normalization block which normalizes all convolved images in the stack. The output of this experiment had the same size as the experiment D-1 output because normalization block did not change the output size. Each output in the stack might have too many different values because of the randomize filter. Batch normalization block could reduce this problem. Experiment D-3 averaged all convolved images to a single image. Both experiment D-1 and D-2 enlarged the output size. This experiment which averaged all pixels in the same position from each output in the stack reduced all output stacks into one image. The output from these experiments was tested with SVM after PCA dimension reduction. Results are shown in Table 4.5.

Table 4-5: Depth convolutional filter testing

Depth	CCR (%)	Features
1	79.00	118x118
2	79.26	118x118x2
4	79.91	118x118x4
8	81.46	118x118x8
16	**81.54**	118x118x16
24	81.17	118x118x24
32	80.60	118x118x32

All experiments had set parameters as filter size 3x3 with depth 16 because filter size 3x3 had the best performance in Table 4.3 and depth 16 had the best performance in Table 4.5. Person model was trained with three different sets, this included one normal walk, four normal walking and three mixed appearances. All the rest from each training set were used as testing set. If one normal walking was used as a training set then five normal walks, two with a coat and two carrying a bag were used as testing set.

Table 4-6: CGI summarize results (conv-convolutional and norm-normalization)

Input	Appear-ance	Training Dataset								
		Conv			Conv and Norm			Average Conv and Norm		
		1 Normal	4 Normal	3 Mixed	1 Normal	4 Normal	3 Mixed	1 Normal	4 Normal	3 Mixed
GEI	Normal	**95.37**	99.11	**94.89**	**96.39**	**99.32**	95.58	**96.62**	**99.38**	**95.79**
	Bag	60.62	71.27	95.11	67.37	79.19	96.33	72.28	81.10	96.65
	Coat	47.41	55.22	**98.26**	53.75	62.56	**99.15**	57.08	64.97	**99.25**
	Mixed	67.80	75.20	**96.09**	72.51	80.36	97.02	**75.33**	**81.82**	**97.23**
GEnI	Normal	95.17	**99.15**	94.69	96.35	99.18	**95.84**	96.35	99.20	95.77
	Bag	**68.65**	**80.22**	**95.50**	**74.61**	**84.67**	**96.71**	**76.67**	**85.62**	**96.83**
	Coat	**51.01**	**59.24**	98.06	**55.67**	**65.20**	99.01	**58.93**	**67.69**	**99.25**
	Mixed	**71.61**	**79.54**	96.08	**75.54**	**83.02**	**97.19**	**77.32**	**84.17**	**97.28**
GGI	Normal	94.70	99.05	85.95	95.20	99.03	88.34	95.03	99.11	89.34
	Bag	37.56	47.47	82.34	39.87	53.50	84.89	43.76	58.04	85.64
	Coat	20.33	29.24	86.50	20.02	31.00	89.55	21.23	32.33	90.55
	Mixed	50.86	58.59	84.93	51.70	61.18	87.59	**53.34**	**63.16**	**88.51**
GGEnI	Normal	94.66	98.95	87.76	95.14	98.95	89.48	94.51	99.05	89.46
	Bag	45.71	57.88	84.17	47.83	61.08	86.13	48.84	62.95	86.38
	Coat	22.20	31.83	88.90	21.76	32.56	90.78	21.87	33.13	90.94
	Mixed	54.19	62.89	86.94	54.91	64.20	88.80	**55.07**	**65.04**	**88.93**

Results from Experiment D demonstrated that the average convolutional and normalization blocks had the best CCR on mixed appearance testing, followed by convolutional and normalize blocks and a single convolutional block in order. The results of each representation were the same pattern as the previous Chapter which average technique has higher accuracy rate than Gaussian technique and entropy technique can increase more robustness to appearance change. As it can be seen in Table 4.6, the correct classification rate (CCR) of experiment D-3 was the best followed by experiment D-2 and D-1 respectively. GEnI had the best recognition followed by GEI, GGI and GGEnI in order. The best CCR rate for mixed appearance testing with one normal walk, four normal walking and mixed appearance training were respectively 77.32%, 84.15% and 97.28. When the training set used only normal walking samples, all of the representations still had a problem with bag and coat appearance, especially walking with a coat had much lower accuracy rate than the other appearance.

4.1.4 Discussion

Experiment A focused on combination variety of CNN computational blocks as gait feature extractor. The output from these combination blocks was used as SVM input for personal model training and personal recognition. The constructed architecture was similar to CNN architecture in its forward propagation.

A number of layers depended on the type of computational blocks and their parameters. Results from Experiment A suggest that:

- A small filter size with a large stride was better than large filter size with a small stride.
- It is better to increase the stride size in a convolutional block instead of pooling block.
- Pooling blocks rapidly reduced output size, however, some information is lost in the trade-off.
- Enlarging filter size can reduce the number of layers and increase the classification rate.

Experiment B which had a similar architecture to A-6 focused on output from each layer. Experimental results showed a smaller combination of computational blocks or fewer layers had higher classification rate. A single combination of each computational block (B-5) had the best CCR at 95.67%.

As suggested in experiment A, pooling block caused a lot of information loss. Experiment C used a single convolutional block and combination of convolutional and normalization block. The results from both architectures were better than the results from experiments B in gait recognition. This experiment also tested filter size. It confirmed experiment A's suggestion. Filter size 3x3 with two computational block combinations had the highest CCR of 97.88%.

All experiments A, B and C tested with three mixed appearance training datasets. Experiment D which trained personal model with normal walking dataset focused on classifier comparison between CNN and SVM. This experiment which fully trained CNN as classifier also tested output from each CNN layer with SVM. All information from each layer was calculated with the bias parameter from CNN. SVM always had better classification rate than CNN. It achieved its highest result at 76.72%.

From all experiments, convolutional and normalization block had been chosen to generate the new gait representations called Convolutional Gait Image or CGI. Nonetheless, the output from both computational blocks which had a larger size than basic representation was the stack images. Thus the average of the stack images was created as a compact image by a mean function. Experiment D trained and tested all convolutional gait representation images by the general gait recognition framework in Figure 4.1. Classification rate of experiment D had been compared with those from their corresponding basic representations in Chapter 3. Single convolutional block had quite a similar classification rate with that from the basic representations while two computational blocks had a better classification rate than that from the basic representations. Averaged output in experiment D-3 had the best classification rate in this experiment. Nevertheless, CGI still had an apparent change problem, especially for the Gaussian representation images. GEnI had the best classification rate in this experiment.

4.2 Gradient Histogram Gait Energy Image (GHGI)

A new gait representation, Gradient Histogram Gait Energy Image (GHGI) is discussed in this section. GHGI is obtained by applying a Histogram of Oriented Gradients technique to compact gait image.

4.2.1 GHGI algorithms

GHGI is obtained by applying the histogram of oriented gradients (HOG) to each input original image then all output frames are averaged to generate the gait representation image [121]. Differently, HOG is applied to basic gait representation images, such as GEI in this study to generate GHGI.

GHGEI is computed in the following steps.

Step 1: Compute horizontal and vertical gradient value I_x and I_y.

Step 2: Compute magnitude r and orientation θ has been computed:

$$r = \sqrt{I_x^2 + I_y^2} \tag{4.6}$$

$$\theta(x, y) = \mathrm{atan}(\frac{I_x}{I_y}) \tag{4.7}$$

Step 3: Calculate cell histogram from each pixel in a cell which is a non-overlapping square region. Each cell typically presents n bin histograms

$$\hat{\theta} = \left\lfloor \frac{n.\theta(x,y)}{2\pi} \right\rfloor \tag{4.8}$$

Cells are grouped into a block which has typically overlap with neighbouring blocks. Each block, which contains 4 cells, has represented a feature of length 36 after each cell has been normalized by L1 norm.

Step 4: Combine feature vectors of all blocks which are normalized by lower-style clipped L2 norm (L2-hys)[122].

4.2.2 Evaluation and Configuration

Dalal and Triggs [122] suggested the optimized HOG parameters, for example, number of orientation histogram bins as 9, which are usually used as the reference for HOG parameters in human detection research. Research [37, 121] and scientific program, for example, MATLAB, refer to these parameters as default settings in applications of HOGs. However in the experiment by using GHGI, which is generated from the grayscale gait compact image, the gait recognition performance does not reach the maximum potential with these default settings. This experiment aims to find the optimized parameters for the HOG method. There are three interesting parameters, cell size, block size, and the number of bins.

All GHGI experiments were conducted on MATLAB which already provided a HOG function named extractHOGFeatures. Experiments 1-3 use GEI as a basic gait representation. The personal model was trained by normal walking appearance while the classification rate was tested by all appearances. Next, four gait representations include GEI, GEnI, GGI and GGEnI in Chapter 3 were operated with HOG in the GHGI experiment.

The first experiment was for cell size testing in which block size and a number of bins were fixed as two and nine, respectively. A number of training samples per person were also considered in this experiment. Among the 6 normal walking samples of each person, 1, 2, 3 or 4 samples were taken for training. Six samples per person, two samples from each appearance, were used as testing samples. The classification rates are shown in Table 4.7.

Table 4-7: GHGI cell size testing

Cell size	Number of training samples			
	1	2	3	4
1	78.29	90.45	91.34	92.46
2	79.69	**91.31**	**91.39**	**92.46**
3	**82.52**	90.70	90.84	92.03
4	76.06	89.50	89.69	91.16
5	70.31	88.66	89.03	90.62
6	71.34	88.07	88.37	90.35
7	70.54	87.21	87.84	89.77
8	69.32	85.95	86.08	88.58

Table 4-8: GHGI Block size testing

Block Size	Number of training samples			
	1	2	3	4
1	83.14	90.97	91.42	92.58
2	84.47	90.97	91.37	92.46
3	**85.67**	**91.23**	**91.47**	**92.79**
4	85.30	91.05	91.43	92.65
5	84.99	90.97	91.39	92.60

Table 4-9: Example of GHGI Number of gradient histogram bins testing with one training sample

Bins	Rate %	Bins	Rate %	Bins	Rate %
1	60.99	13	86.64	25	84.37
2	71.37	14	86.08	26	84.47
3	79.43	15	85.09	27	85.36
4	82.13	16	86.93	28	84.55
5	83.69	17	83.94	29	83.50
6	85.03	18	84.94	30	83.63
7	86.19	19	85.34	31	81.41
8	85.31	20	85.94	32	81.66
9	84.14	21	84.41	33	83.12
10	86.53	22	86.61	34	83.20
11	86.96	23	84.50	35	82.53
12	**87.42**	24	85.27	36	79.10

The optimized cell size for one training dataset was three while the rest was two. After this optimized point, the classification rate dropped continually. The cell size of two was set up as an initial parameter for the second experiment of block size testing. The number of bins was fixed as nine, the same as in the first experiment. Results are shown in Table 4.8.

The optimized block size is three. If block size is above three, the classification rate drops. Next, both cell size and block size are fixed to find the optimized number of bins. The results for a number of bins testing are shown in Table 4.9 and Figure 4.7. It had the highest score of 87.42 with 12 bins. The next highest scores for two, three and four training samples are 92.47% (19 bins), 92.35% (25 bins) and 93.03% (16 bins). The optimized number of bins was calculated from averaged of a number of training samples was fifteen. In summary, the optimized parameters for HOG method which was used in the rest of the experiments in this section is shown in Table 4.10.

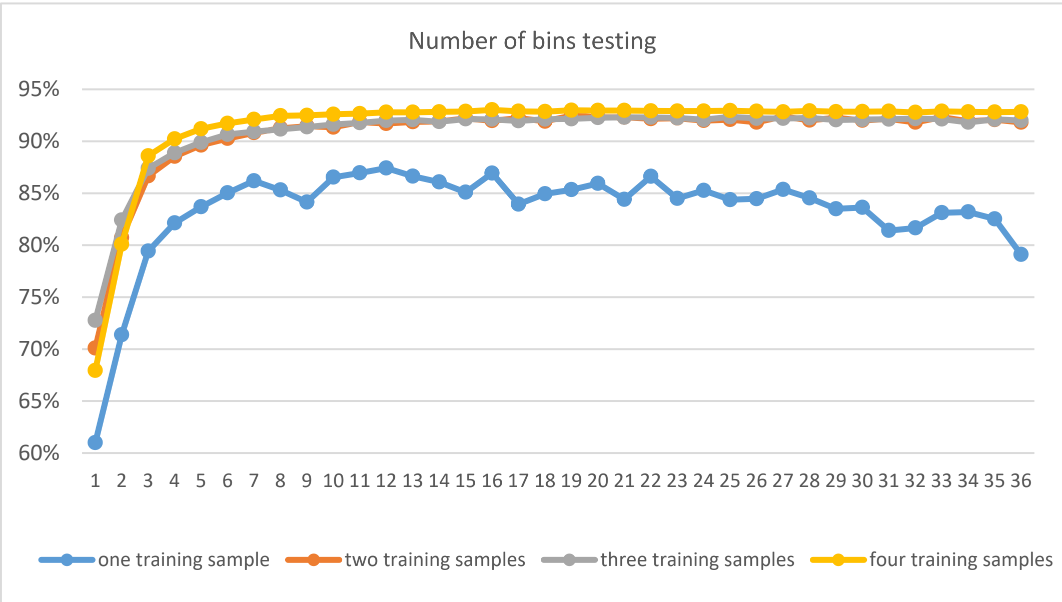


Figure 4-7: Number of bins testing for optimized HOG parameters

Table 4-10: Optimized parameter for GHGI

Parameter	Number of the Training dataset			
	1	2	3	4
Cell Size	3	2	2	2
Block Size	3	3	3	3
Bins	15	15	15	15

From the results demonstrated in Tables 4.6 - 4.9 and Figure 4.7, apart from one training sample, there is no significant difference w.r.t. classification rate by using two, three or four training samples (only 1-2% difference). Thus two training samples were suggested as the minimum number of training samples. In contrast, one training sample would introduce a lower classification rate, as shown in Figure 4.7. It is interesting that if the parameter values are set high, the performance of GHGI was very low in terms of cell size and a number of bins. The optimized parameters were applied in the other basic gait representations, include GEnI, GGI and GGEnI, demonstrated in the fourth experiment.

The fourth experiment takes the optimized parameter set in Table 4.10, expanded in the HOG method to the other three basic gait representations. It shows that the HOG method can improve the classification rate for the basic gait representations. Table 4.11 shows the classification rate of basic gait representations and Gradient Histogram Gait Image.

Table 4-11: Correct classification rate of Basic Gait Representation and GHGI

Representations	Appearances	Training dataset							
		Basic Representation				GHGI			
		1	2	3	4	1	2	3	4
GEI	Normal	**95.37**	98.68	**99.21**	99.14	**95.24**	98.11	97.86	98.63
	Bag	60.67	68.85	69.95	71.82	**83.83**	**90.88**	**91.31**	**92.30**
	Coat	47.53	54.59	54.62	55.24	**78.15**	**87.19**	**87.01**	**88.45**
	Mixed	67.86	74.04	74.59	75.40	**85.74**	**92.06**	**92.06**	***93.13***
GEnI	Normal	94.99	**98.74**	99.02	**99.15**	94.33	97.69	98.09	98.86
	Bag	**68.54**	**76.49**	**78.07**	**80.81**	81.78	90.48	90.83	**92.15**
	Coat	**51.12**	**57.78**	**57.30**	**60.17**	76.46	86.08	86.25	**87.78**
	Mixed	**71.55**	**77.67**	**78.13**	**80.04**	84.19	91.42	91.72	**92.93**
GGI	Normal	94.93	98.13	98.78	99.09	96.27	**99.28**	**99.63**	**99.73**
	Bag	38.91	43.92	46.67	48.23	67.78	82.13	84.74	**87.39**
	Coat	20.45	26.61	28.72	29.75	41.73	58.95	61.99	**64.78**
	Mixed	51.43	56.22	58.06	59.02	68.60	80.12	82.12	**83.97**
GGEnI	Normal	94.72	98.11	98.65	98.99	95.47	99.00	99.55	**99.73**
	Bag	46.65	54.71	57.33	58.61	66.82	81.25	83.60	**85.67**
	Coat	22.76	28.96	31.51	32.40	38.97	58.60	62.00	**65.13**
	Mixed	54.71	60.59	62.50	63.33	67.09	79.62	81.72	**83.51**

All results were taken from the average of the eleven view angles. GEnI was the best in the basic representations and had the average classification rate of 80.04% with four normal walking training samples. All basic representations had a problem with appearance changes especially GGI and GGEnI which were generated by convolving Gaussian kernels.

HOG can increase the classification rate over almost all basic representations except for the normal walking testing in case of GEI and GEnI. The classification rate in cases of walking with bag and coat was enormously higher than that of basic representations. This shows that when the HOG is applied to the basic representations the new secondary representations are more tolerant to appearance changes. Nonetheless, the classification rate in terms of the normal walking was slightly decreased.

GEI+HOG with four training samples had the highest average classification rate of 93.13%. This confirms that GEI, which was simple and less computation efficient, was the best gait representation when combined with the HOG method.

The detailed classification rate over 11 view angles for the secondary representations is shown in Figure 4.8. The results were from four normal walking training samples. If only normal walking testing was considered, GGI and GGEnI had the best result with the same value in every view angle. The classification rate of 100% at 0°, 18°, 54°, 126°, 144°, 168° and 180° is shown to GGI and GGEnI, while GEI and GEnI had the best classification rate of 99.57% (18°) and 99.89% (54°), respectively.

Nonetheless, GEI and GEnI had the better classification rate in case of walking with bag and coat. Both representations had classification rate with bag higher than 95% in 72°, 90° and 108°. And they had classification rate with coat higher than 90% in 18°, 36° and 54°. If all results from every gait presentation had been calculated together in each view angle, GHGI had the highest classification rate of 91.23% at 72° while basic representations had the highest rate of 65.01% in 180°.

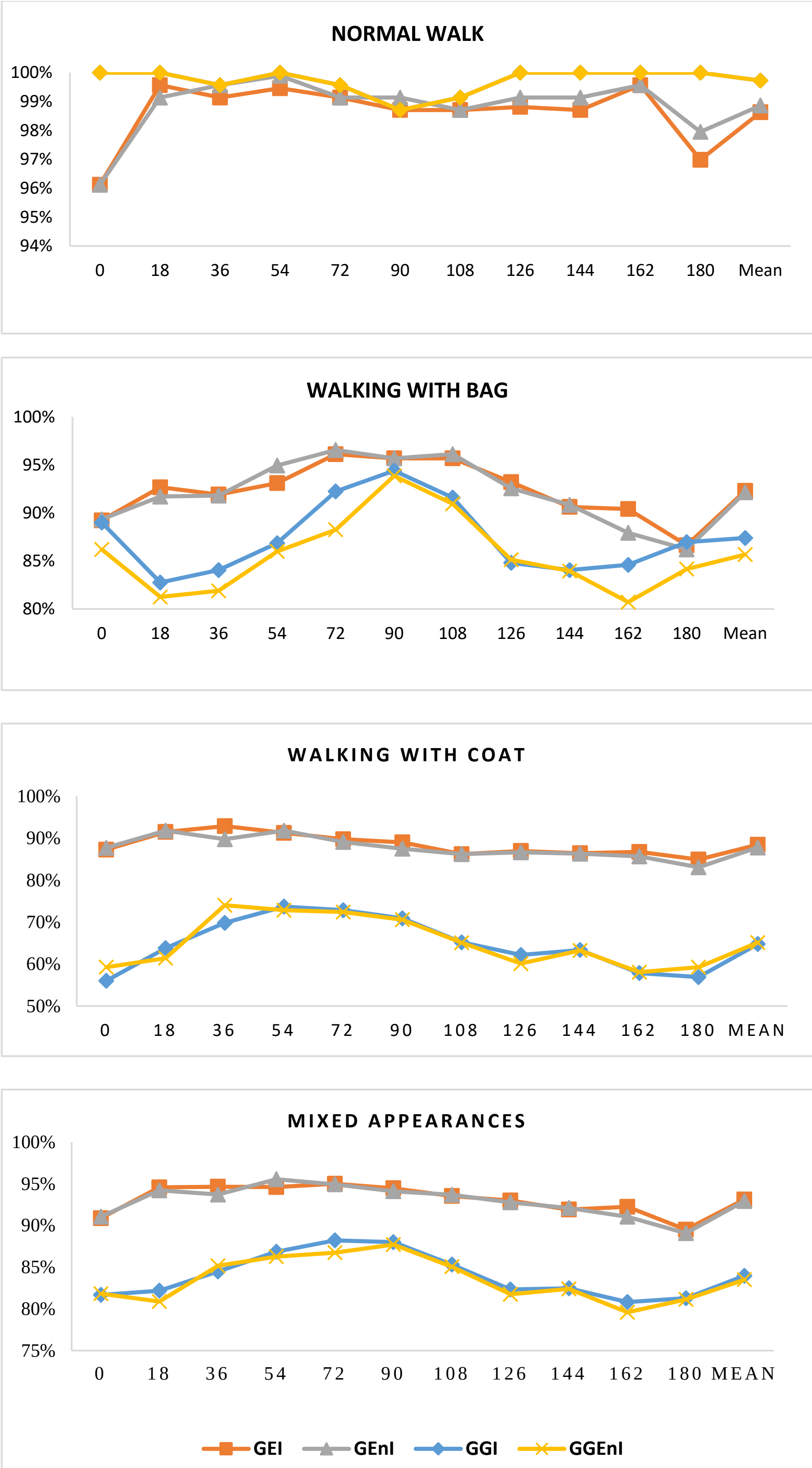


Figure 4-8: Correct classification rate of GHGI with different basic gait representation image

Overall, GHGI had increased the classification rate approximately over 17% - GEI, 12% - GEnI, 24% - GGI and 20% -GGEnI. This confirms that HOG can directly apply to gait compact image and increase their classification rate especially in case of appearance changes.

4.2.3 Discussion

GHGI representations which are generated by directly applying Histogram of Oriented Gradients to basic gait representation images can improve the classification rate. The MATLAB function, called extractHOGFeatures which is implemented by the following suggestions in Dalal and Triggs research [122] set default parameters as 8x8 cell size, 2x2 block size, 50% block overlapped and 9 orientation histogram bins. However, these values did not give the best classification rate for GHGI which was generated from grey scale level compact gait images. Performance of these representations is dependent on parameter settings used in HOG applications.

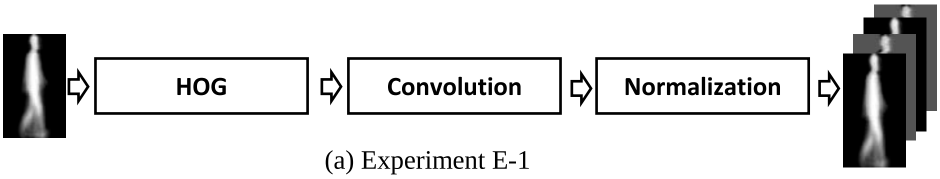
Table 4-12: Example GHGI size

Orientation histogram bins	Cell size	Block size				
		1x1	2x2	3x3	4x4	5x5
9	1x1	101,376	397,764	877,716	390,096	585,900
	2x2	25,344	97,524	210,924	93,744	135,000
	3x3	10,962	41,328	87,480	37,440	55,575
	4x4	6,336	23,436	48,600	21,600	28,350
	5x5	3,825	13,824	27,945	11,088	17,325
15	1x1	168,960	662,940	1,462,860	650,160	976,500
	2x2	42,240	162,540	**351,540**	156,240	225,000
	3x3	18,270	68,880	145,800	62,400	92,625
	4x4	10,560	39,060	81,000	36,000	47,250
	5x5	6,375	23,040	46,575	18,480	28,875

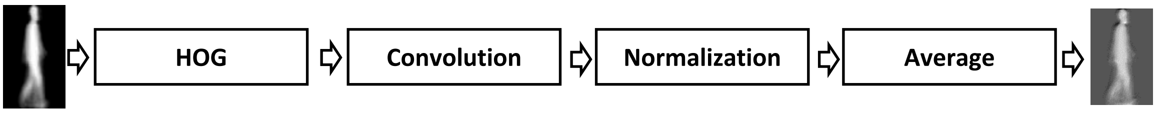
Experiments 1-3 in this section were separately conducted by three parameters, i.e. cell size, and block size and orientation histogram bins. When cell size and block size decrease, small-scale details in basic gait representations are captured. When the number of orientation histogram bins increases, finer orientation details are captured. However, they need more computational time. From the experiments, the optimized parameter settings are worked out as 2x2 cell size, 3x3 block size and 15 bins for the CASIA dataset B, except the case of using one training sample. These secondary gait representations using the optimized HOG parameters are more tolerant to appearance changes as can be seen from Table 4.11. GHGI which was generated from GEI had the best average classification rate of 85.74% of one training sample and 93.13% of four training samples. GHGI had increased the classification rate approximately over 17% - GEI, 12% - GEnI, 24% - GGI and 20% - GGEnI. This study is focused on the CASIA gait dataset B, optimized parameters may vary to other gait datasets, to which more fine adjustments and testing could be conducted to achieve an optimized result. The example of typical GHGI size with a basic gait representation size of 128x88 pixels is shown in Table 4.12.

4.3 Convolutional Gradient Histogram Gait Image (CGHGI)

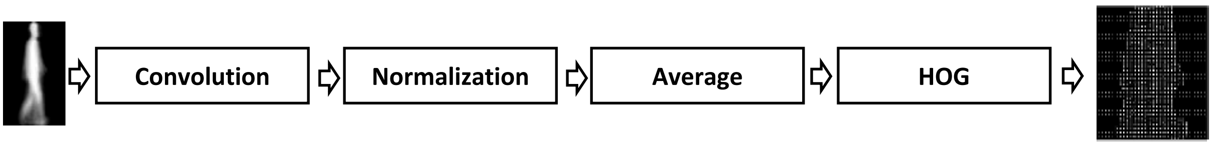
Both convolutional and Histogram of Oriented Gradients representations in section 4.1 and 4.2 improve the gait recognition accuracy rate over that of the basic gait representations. Both representations can be used as input for each other to produce alternative representations. In this section, the combination of both techniques is studied as it can be seen in Figure 4.8.



(a) Experiment E-1



(b) Experiment E-2



(c) Experiment E-3

Figure 4-9: Convolutional Gradient Histogram Gait Image

HOG input and output are respectively a TrueColor or grey scale image and extracted HOG feature vector. While convolutional block input and output are an image stack which has a number of members in stack equal to the depth value. For example, the RGB image has three different channels. If RGB colour is used as input for the convolutional block, it must change to image stack in which each image represents the red, green and blue colour. And convolved output depth depends on filter depth. If the output from HOG or convolutional block is considered, it cannot directly feed as input for another technique. They must reorganize to a suitable format.

Both combination E-1 and E-2 need to reformat output from HOG into image stack in which each image represents information in each orientation histogram bin. The number of filters is set to the same number of orientation histogram bins. For instance, GHGIs which were generated by a 9-bin setting were reformatted into 9 images in the same stack. If the convolutional kernel is 3x3 and output from convolutional operations is set to 16 images in the stack, filter size is set to 3x3x**9**x16 in this case.

Combination E-3 starts with a convolutional block which uses filter size is 3x3x1x16. Convolved image stack depth is sixteen, then this stack is normalized by batch normalization block. Normalized image stack is averaged into one single image which can be used as the input for HOG method.

4.3.1 Experimental Results

The experiments used four gait compact images GEI, GEnI, GGI and GGEnI as basic gait representation to generate CGHGI. HOG processes took the optimized parameters in Table 4.10. Convolutional processes set its kernel to 3x3 thus experiments E-1 and E-2 used filter size 3x3x15x30 because they used a HOG output which was reformatted to 15 images in the stack. In contrast, experiment E-3 set filter size as 3x3x1x16 then averaged its 16 output images in the stack into one representation image before it was sent to the HOG process. The HOG process used optimized parameters in Table 4.12. Output representation size depended on experiments. Experiment E-1 resulted in 32 images in the stack, Experiment E-2 resulted in one averaged image, and Experiment E-3 resulted in one image which was reformatted from the output vector. All experiment outputs were reduced data dimensions by PCA before passed to SVM processes as it can be seen in Figure 4.1. The number of features after the PCA process depended on the number of training dataset, for instance, 1 training sample with 116 people had 116 values per gait representation after a PCA dimension reduction process. If there are 4 training samples, reduced data was in the size of 4x116 or 364 values after the PCA process. Average classification rate, trained by a different number of training samples, is shown in Table 4.13 to 4.15.

Table 4-13: Experiment E-1 Results

Gait representation	Appearance	Training dataset			
		1	2	3	4
GEI	Normal	95.42	98.16	97.90	98.59
	Bag	**83.64**	**90.83**	**91.16**	92.08
	Coat	**77.98**	**87.05**	**86.97**	**88.36**
	Mixed	**85.68**	**92.01**	**92.01**	**93.01**
GEnI	Normal	94.35	97.73	98.09	98.82
	Bag	82.62	90.36	90.73	**92.20**
	Coat	76.65	85.93	86.13	87.19
	Mixed	84.54	91.34	91.65	92.74
GGI	Normal	**95.89**	**99.31**	**99.70**	99.69
	Bag	66.34	82.97	84.99	86.48
	Coat	36.44	59.11	62.75	63.52
	Mixed	66.22	80.47	82.48	83.23
GGEnI	Normal	95.55	**99.31**	99.57	**99.73**
	Bag	66.63	81.52	83.03	85.15
	Coat	41.18	58.88	62.01	63.56
	Mixed	67.79	79.90	81.54	82.81

Table 4-14: Experiment E-2 Results

Gait representation	Appearance	Training dataset			
		1	2	3	4
GEI	Normal	94.76	97.73	97.60	98.55
	Bag	80.84	**89.69**	**89.66**	**91.65**
	Coat	75.24	**86.60**	85.74	**87.46**
	Mixed	83.61	**91.34**	**91.00**	**92.55**
GEnI	Normal	93.95	97.24	97.96	98.63
	Bag	**81.62**	89.22	89.26	91.22
	Coat	**75.55**	84.99	**85.78**	86.52
	Mixed	**83.71**	90.48	**91.00**	92.12
GGI	Normal	**96.14**	**99.00**	**99.24**	**99.53**
	Bag	64.77	78.57	81.62	83.39
	Coat	36.76	56.58	59.60	61.95
	Mixed	65.89	78.05	80.15	81.62
GGEnI	Normal	95.06	98.80	99.03	99.49
	Bag	63.44	75.08	79.35	81.47
	Coat	37.70	54.70	58.82	62.62
	Mixed	65.40	76.20	79.07	81.19

Results from Experiments E-1, E-2 and E-3 had the same pattern. When GEI was used as the basic gait representation in case of mixed appearance testing, it had the highest classification rate of 93.01% with four normal walking training dataset. If a number of training samples were separately considered, the best classification rate in each size was 85.68% one training dataset with GEI-E1, 92.01% two training dataset with GEI-E1, 92.01% three training dataset with GEI-E1 and 93.01% four training dataset with GEI-E1. The results presented in the three tables had the same pattern with GHGI. The average technique includes GEI and GEnI had a better rate than the Gaussian technique. GEI had the best classification rate. However, maximum GEI-E1 had lower classification rate than GHGI in Table 4.11.

Table 4-15: Experiment E-3 Results

Gait representation	Appearance	Training dataset			
		1	2	3	4
GEI	Normal	62.05	95.08	95.77	98.67
	Bag	51.06	82.09	82.64	91.73
	Coat	47.26	**81.07**	**81.47**	**88.52**
	Mixed	53.46	**86.08**	86.62	**92.97**
GEnI	Normal	70.86	95.00	95.45	98.86
	Bag	**57.25**	**83.58**	**84.44**	**91.77**
	Coat	**52.55**	79.66	80.13	87.85
	Mixed	**60.22**	**86.08**	**86.68**	92.83
GGI	Normal	69.28	96.73	98.35	**99.73**
	Bag	43.14	68.22	72.45	85.70
	Coat	23.32	44.20	47.37	63.52
	Mixed	45.25	69.72	72.73	82.98
GGEnI	Normal	**71.03**	**97.36**	**98.64**	**99.73**
	Bag	42.99	69.79	73.63	85.27
	Coat	23.47	43.81	47.81	63.87
	Mixed	45.83	70.32	73.36	82.95

4.3.2 Discussion

The new gait representation, which combines both convolutional and HOG techniques in the secondary representation generation, had a slightly lower average classification rate than GHGI. From the computational point of view, the combination in E-2 had enormously reduced data size as it can be seen in Table 4.16. Additionally, the convolutional process in this study used the randomize filter. It is possible to optimize filter or kernel parameters to achieve better results. This could be done as future work.

Table 4-16: Number of CGHGI data

Representation	Basic	CGI		GHGI	CGHGI		
		D-1/D-2	D-3		E-1	E-2	E-3
Number of data	11,264 (128x88)	173,376 (126x86x16)	10,836 (126x86)	351,540 (186x126x15)	684,480 (184x124x30)	22,816 (184x124)	337,635 (183x123x15)

4.4 View classification

The second experiment used the same setting as in the first experiment. The main difference was the input gait representations. The four basic compact gait images, GEI, GEnI, GGI, and GGEnI, were used to generate three kinds of gait representations, i.e. CGI, GHGI and CGHGI as described in Chapter 4. These representations were passed to the view angle classification system. Results from all appearances are shown in Table 4.17.

Table 4-17: Average view angle classification rate by CGI, GHGI, and CGHGI

View Angle	CGI				GHGI				CGHGI			
	GEI	GEnI	GGI	GGEnI	GEI	GEnI	GGI	GGEnI	GEI	GEnI	GGI	GGEnI
0	90.95	88.79	93.32	96.19	96.26	96.98	**99.14**	98.42	96.12	96.41	97.56	97.13
18	91.52	92.10	94.61	97.41	96.41	96.84	99.43	99.14	95.26	96.34	**99.57**	99.43
36	94.63	94.76	97.41	97.05	95.26	95.26	**98.99**	98.85	94.90	94.76	98.85	98.71
54	88.51	91.45	94.54	97.20	96.55	96.84	**98.71**	**98.71**	96.41	95.98	**98.71**	98.56
72	92.41	93.53	92.74	93.61	96.26	95.83	**97.27**	96.98	95.55	95.11	96.26	95.98
90	78.13	83.98	80.68	90.73	93.68	93.97	**96.84**	96.70	92.60	92.96	94.83	94.68
108	85.49	88.43	90.45	92.39	95.55	96.12	**97.13**	**97.13**	96.26	96.34	**97.13**	96.41
126	94.68	93.53	92.82	96.77	97.56	97.84	98.85	98.99	97.63	98.06	**99.28**	99.28
144	91.70	90.59	93.75	93.39	95.98	96.12	**97.41**	97.13	96.26	96.05	**97.41**	97.27
162	86.87	91.38	95.62	96.84	95.40	94.83	**96.70**	**96.70**	95.62	95.26	96.41	**96.70**
180	90.32	90.95	92.67	96.12	94.54	93.53	96.70	**97.27**	92.60	92.31	96.41	96.12
Means	89.56	90.86	92.60	95.25	95.77	95.83	**97.92**	97.82	95.38	95.42	97.49	97.30

From the results in Table 4.17, the three kinds of representations improved the view angle classification rate when compared with those in Table 3.3. GHGI gave the most improvement. The best view angle classification rate was 97.92% by GHGI-GGI followed by 97.82%-GGEnI.

4.5 Summary

This Chapter presents three secondary gait representations, i.e. Convolutional Gait Image (CGI), Gradient Histogram Gait Image (GHCI) and Convolutional Gradient Histogram Gait Image (CGHGI). Three types of CGI experiments were conducted: convolutional (D-1), convolutional plus normalization (D-2), and convolutional plus normalization plus average (D-3). CGHGI which combined convolutional and Histogram of Oriented Gradients techniques had three different combinations: HOG plus D-2 (E-1), HOG plus D-3 (E-2) and D-3 plus HOG (E-3). Summarized classification rate which is average of eleven view angles is shown in Table 4.18, 4.19 and 4.20.

Table 4-18: Summarized correct classification rate in case of one normal walking training dataset

Basic Representation	Appearance	Representation							
		Basic	CGI			GHGI	CGHGI		
			D-1	D-2	D-3		E-1	E-2	E-3
GEI	Normal	95.37	95.37	96.39	**96.62**	95.24	95.42	94.76	62.05
	Bag	60.67	60.62	67.37	72.28	**83.83**	83.64	80.84	51.06
	Coat	47.53	47.41	53.75	57.08	**78.15**	77.98	75.24	47.26
	Mixed	67.86	67.80	72.51	**75.33**	**85.74**	85.68	83.61	53.46
GEnI	Normal	94.99	95.17	96.35	96.35	94.33	94.35	93.95	70.86
	Bag	68.54	68.65	74.61	76.67	81.78	82.62	81.62	57.25
	Coat	51.12	51.01	55.67	58.93	76.46	76.65	75.55	52.55
	Mixed	71.55	71.61	75.54	**77.32**	84.19	84.54	83.71	60.22
GGI	Normal	94.93	94.70	95.20	95.03	96.27	95.89	96.14	69.28
	Bag	38.91	37.56	39.87	43.76	67.78	66.34	64.77	43.14
	Coat	20.45	20.33	20.02	21.23	41.73	36.44	36.76	23.32
	Mixed	51.43	50.86	51.70	**53.34**	68.60	66.22	65.89	45.25
GGEnI	Normal	94.72	94.66	95.14	94.51	95.47	95.55	95.06	71.03
	Bag	46.65	45.71	47.83	48.84	66.82	66.63	63.44	42.99
	Coat	22.76	22.20	21.76	21.87	38.97	41.18	37.70	23.47
	Mixed	54.71	54.19	54.91	**55.07**	67.09	67.79	65.40	45.83

GHGI-GEI had the best classification rate for a mixed appearance in the three tables: 85.74%-one normal walking training dataset, 93.13%-four normal walking training datasets and 98.03%-mixed appearance training datasets. The best classification rate when tested by normal walking was 96.62%-CGI-E3-GEI for one training dataset, 99.73%-GHGI-GGI for four training datasets and 98.74%-GHGI-GGI mixed appearance datasets. The best classification rate when tested by walking with a bag was 83.83%-GHGI-GEI for one training dataset, 92.30%-GHGI-GEI for four training datasets and 99.06%-CGHGI-E1-GEI for mixed appearance datasets. The best classification rate when tested by walking with a coat was 78.15%-GHGI-GEI for one training dataset, 88.52%-CGHGI-E3-GEI for four training datasets and 99.84%-CGHGI-E1-GEnI for mixed appearance datasets. All results have shown that GHGI from GEI is the best representation in this Chapter. The randomized filter in the convolutional process may cause the low performance in CGHGI. From the next Chapter onward, only GEI is used as the basic gait representation to generate secondary gait representations.

Table 4-19: Summarized correct classification rate in case of four normal walking training datasets

Basic Representation	Appearance	Representation							
		Basic	CGI			GHGI	CGHGI		
			D-1	D-2	D-3		E-1	E-2	E-3
GEI	Normal	99.14	99.11	99.32	99.38	98.63	98.59	98.55	98.67
	Bag	71.82	71.27	79.19	81.10	**92.30**	92.08	91.65	91.73
	Coat	55.24	55.22	62.56	64.97	88.45	88.36	87.46	**88.52**
	Mixed	75.42	75.20	80.36	81.82	**93.13**	93.01	92.55	92.97
GEnI	Normal	99.15	99.15	99.18	99.20	98.86	98.82	98.63	98.86
	Bag	80.81	80.22	84.67	85.62	92.15	92.20	91.22	91.77
	Coat	60.17	59.24	65.20	67.69	87.78	87.19	86.52	87.85
	Mixed	80.04	79.54	83.02	84.17	92.93	92.74	92.12	92.83
GGI	Normal	99.09	99.05	99.03	99.11	**99.73**	99.69	99.53	99.73
	Bag	48.23	47.47	53.50	58.04	87.39	86.48	83.39	85.70
	Coat	29.75	29.24	31.00	32.33	64.78	63.52	61.95	63.52
	Mixed	59.02	58.59	61.18	63.16	83.97	83.23	81.62	82.98
GGEnI	Normal	98.99	98.95	98.95	99.05	**99.73**	**99.73**	99.49	99.73
	Bag	58.61	57.88	61.08	62.95	85.67	85.15	81.47	85.27
	Coat	32.40	31.83	32.56	33.13	65.13	63.56	62.62	63.87
	Mixed	63.33	62.89	64.20	65.04	83.51	82.81	81.19	82.95

Table 4-20: Summarized correct classification rate in case of mixed appearance training dataset

Basic Representation	Appearance	Representation							
		Basic	CGI			GHGI	CGHGI		
			D-1	D-2	D-3		E-1	E-2	E-3
GEI	Normal	95.25	94.89	95.58	95.79	95.29	95.13	94.67	94.86
	Bag	95.22	95.11	96.33	96.65	99.02	**99.06**	98.75	98.90
	Coat	98.39	98.26	99.15	99.25	99.76	99.69	99.61	99.76
	Mixed	96.29	96.09	97.02	97.23	**98.03**	97.96	97.68	97.84
GEnI	Normal	94.77	94.69	95.84	95.77	95.43	95.31	94.36	94.81
	Bag	95.67	95.50	96.71	96.83	98.57	98.47	98.04	98.59
	Coat	97.96	98.06	99.01	99.25	99.80	**99.84**	99.37	99.76
	Mixed	96.14	96.08	97.19	97.28	97.93	97.88	97.26	97.72
GGI	Normal	86.28	85.95	88.34	89.34	**98.74**	98.63	96.91	98.24
	Bag	82.18	82.34	84.89	85.64	96.20	96.08	93.73	96.08
	Coat	86.85	86.50	89.55	90.55	98.61	98.51	97.26	98.35
	Mixed	85.10	84.93	87.59	88.51	97.85	97.74	95.97	97.56
GGEnI	Normal	88.24	87.76	89.48	89.46	98.37	98.35	96.03	98.32
	Bag	84.39	84.17	86.13	86.38	95.94	95.77	93.10	95.85
	Coat	89.48	88.90	90.78	90.94	98.16	98.16	96.63	98.12
	Mixed	87.37	86.94	88.80	8.93	97.49	97.43	95.26	97.43

In addition, GEI has performed as the best basic presentation in the experiments in this Chapter. The comparison of basic GEI classification rate in each view angle is shown in Table 4.21. GHGI-GEI had the best classification rate in case of mixed appearance testing, although it did not have the best classification rate for every view angle. The best classification rate in sequence view angle were 91.38%-CGHGI-E1, 94.58%-GHGI, 94.68%-CGHGI-E1, 94.61%-GHGI, 95.69%-CGHGI-E3, 94.47%-GHGI, 93.82%-CGHGI-E3, 93.00%-GHGI, 91.92%-GHGI, 92.24%-GHGI and 90.23%-CGHGI-E3. The highest classification rate for mixed appearance testing was 95.69% CGHGI-E3 at 72°. The best average classification rate for normal walking testing was 99.38%-CGI-D3, and the best view angle for normal walking testing was 18° with a classification rate of 100% for GEI/CGEI. The best average classification rate for walking with a bag was 92.30%-GHGI while the best view angle for walking with a bag was 72° with 96.55% CGHGI-E-3. The best average classification rate for walking with a coat was 88.52%-CGHGI-E3 while the best view angle for walking with a coat was 36° with 96.55% CGHGI-E-3.

The extended gait representations, i.e. CGI, GHGI and CGHGI, are generated from the four basic gait compact images used in the first experiment. The convolutional technique can slightly improve the classification rate while HOG technique enormously increases the classification rate. Combined convolutional and HOG technique has lightly lower classification rate than HOG technique. The Gaussian technique has better classification rate than average technique however the gap between both techniques are removed by HOG technique as it can be seen from GHGI and CGHGI results in Table 4.16. HOG also beats the advantage of entropy technique in case of Gaussian technique as it can be seen from GHGI-GGI and GHGI-GGEnI comparison and CGHGI-GGI and CGHGI-GGEnI comparison.

Chapter 3 and this Chapter focus on the gait representation. The detail of all gait represents generation processes are already explained. However, all experiments use the full silhouette to generate the gait representation. When people walk, the locomotion for body parts such as head, hand and leg are not the same. In the next Chapter, the partial body gait recognition is explored with all gait representations which relates to GEI representation, because GHGI-GEI has the best recognition in this Chapter.

Table 4-21: CCR of GEI and derived GEI gait presentation in separate view angle

Representation		Appearance	view angle											
			0	18	36	54	72	90	108	126	144	162	180	Mean
GEI		Normal	99.57	**100.0**	99.57	98.71	98.71	99.14	99.14	99.14	98.71	98.71	99.14	99.14
		Bag	77.07	72.59	76.55	66.03	66.03	67.50	70.69	68.71	71.21	72.41	79.83	71.69
		Coat	47.76	58.36	55.26	60.78	57.93	59.48	58.53	54.05	53.88	51.90	51.90	55.44
		Mixed	74.80	76.98	77.13	75.17	74.22	75.37	76.12	73.97	74.60	74.34	76.95	75.42
CGI	D-1	Normal	99.57	**100.0**	99.57	98.71	98.71	99.14	99.14	99.14	98.36	98.79	99.14	99.11
		Bag	76.72	73.19	74.91	65.52	65.86	66.81	70.17	69.57	70.09	72.16	78.97	71.27
		Coat	48.28	58.36	55.60	60.43	57.33	59.22	57.67	54.57	53.10	51.98	50.86	55.22
		Mixed	74.86	77.18	76.70	74.89	73.97	75.06	75.66	74.43	73.85	74.31	76.32	75.20
	D-2	Normal	99.74	**100.0**	99.66	99.05	99.05	99.14	99.14	99.05	98.79	99.40	99.48	99.32
		Bag	80.00	79.57	81.29	74.40	78.97	77.93	79.74	80.34	78.36	78.28	82.24	79.19
		Coat	50.26	62.16	61.81	68.53	69.57	69.91	69.83	62.50	62.16	57.93	53.53	62.56
		Mixed	76.67	80.57	80.92	80.66	82.53	82.33	82.90	80.63	79.77	78.53	78.42	80.36
	D-3	Normal	99.74	**100.0**	99.66	98.97	98.97	99.22	99.22	99.31	99.14	99.40	99.57	**99.38**
		Bag	82.67	81.81	83.19	78.10	80.17	79.83	81.29	81.64	79.83	80.95	82.59	81.10
		Coat	53.19	63.36	65.09	70.60	72.50	72.24	71.38	66.64	63.97	59.48	56.21	64.97
		Mixed	78.53	81.72	82.64	82.56	83.88	83.76	83.97	82.53	80.98	79.94	79.45	81.82
GHGI		Normal	96.12	99.57	99.14	99.46	99.14	98.71	98.71	98.81	98.71	99.57	96.98	98.63
		Bag	89.22	92.67	91.92	93.10	96.12	95.69	95.69	93.21	90.63	90.41	86.64	**92.30**
		Coat	87.28	91.49	92.89	91.27	89.76	89.01	86.21	86.96	86.42	86.75	84.91	88.45
		Mixed	90.88	**94.58**	94.65	**94.61**	95.01	**94.47**	93.53	**93.00**	**91.92**	**92.24**	89.51	**93.13**
CGHGI	E-1	Normal	96.55	99.14	99.14	99.57	99.14	98.71	98.71	98.71	98.71	99.14	96.98	98.59
		Bag	89.22	91.81	91.81	92.67	96.12	95.69	95.26	93.10	90.09	90.52	86.64	92.08
		Coat	88.36	90.52	**93.10**	90.95	90.52	88.79	86.64	86.21	86.64	86.21	84.05	88.36
		Mixed	**91.38**	93.82	**94.68**	94.40	95.26	94.40	93.53	92.67	91.81	91.95	89.22	93.01
	E-2	Normal	96.55	99.14	99.57	99.14	98.71	98.71	98.71	98.28	98.71	99.57	96.98	98.55
		Bag	87.93	88.79	92.24	92.24	96.12	95.69	96.12	93.10	90.52	87.93	87.50	91.65
		Coat	86.21	92.67	90.95	90.95	88.79	86.64	85.78	83.19	85.34	85.34	86.21	87.46
		Mixed	90.23	93.53	94.25	94.11	94.54	93.68	93.53	91.52	91.52	90.95	**90.23**	92.55
	E-3	Normal	96.55	99.14	99.14	99.57	99.14	98.71	98.71	99.14	98.71	99.57	96.98	98.67
		Bag	88.36	92.24	91.38	93.10	**96.55**	95.26	95.69	92.67	88.36	89.22	86.21	91.73
		Coat	87.50	91.38	91.38	90.52	91.38	88.79	87.07	87.07	86.64	87.07	84.91	**88.52**
		Mixed	90.80	94.25	93.97	94.40	**95.69**	94.25	**93.82**	92.96	91.24	91.95	89.37	92.97

Chapter 5 Investigation of partial body gait representation

When a person is walking, the various body parts moves at different speeds and directions. These movements depend on the individual and they can be used to identify the person. In the model free approach, sequential images can be combined into one compact image which represents all motion information, for example, Gait Energy Image (GEI) or Gait Gaussian Image (GGI) as described in Chapter 3. This representation image is generated from black and white or silhouette images. Nevertheless, the shape of a silhouette image varies due to clothing, accessories or carrying objects. This problem leads to fault recognition when full silhouette is used in a recognition system. On the other hand, some body parts may be less influenced by different clothing etc. Consequently, the silhouette may not change much no matter if the person carries an object or not. For example, the movement of lower knees may not be affected by carrying a back-pack. If only these body parts are considered instead of the full body, the classification rate may be improved. However which body parts should be used in a gait recognition system? Finding answers to the question motivates the experiments in this Chapter which can be divided into five main experiments. The first is a single body part which uses only one selected body part to identify a person. The second is the score fusion from two body parts which are selected in the training and testing phase. The scores of both parts are fused together after the SVM prediction process. The third is the image fusion which directly concatenates two selected parts into a single image. The fourth is to create a multi-region duplicate image which is similar with image fusion. Nonetheless, one part is duplicated more than one time in the image fusion. More details are presented in the following sections. The last is view variations which have two experiments including view classification and cross view gait recognition. Every single body part is used in both experiments

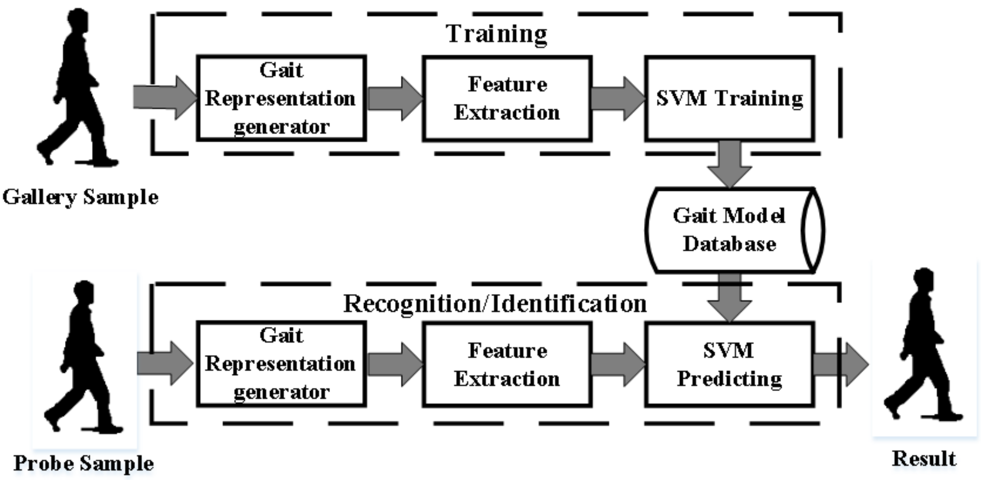


Figure 5-1: Anthropometric Measurement and Different Partial Silhouette

5.1 Single Part Gait Representation

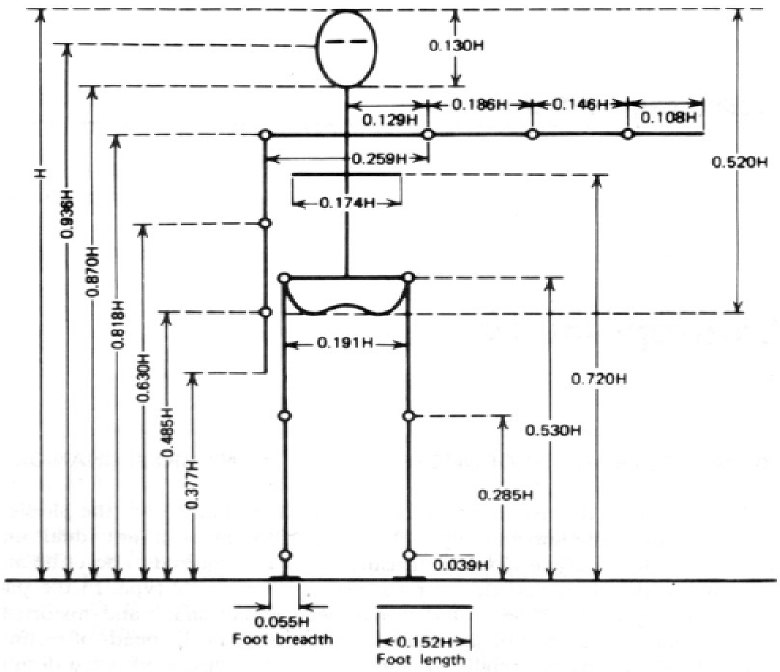
This section tests the effect of each body part in gait recognition. The human body is divided into twelve different parts based on average anthropometric measurement [48]. Each part is used as an input to the recognition system, as shown in Figure 5.1. Input image sequences are processed to create Gait Energy Image (GEI). Then GEI is used to generate three compact images as described in Chapter 4, i.e. CGI, GHGI and CGHGI. CGI D-3, archeved the highest recognition scores in Table 4.18, these are chosen in this Chapter. Next, gait features are extracted from the compact images by Principal Component Analysis (PCA). Then the personal model is trained by one-against-all Support Vector Machine (SVM) in the training phase. The gait features are also used to identify a person by SVM in the recognition phase. The highest score is selected as the recognition result.

5.1.1 Average Anthropometric Measurement

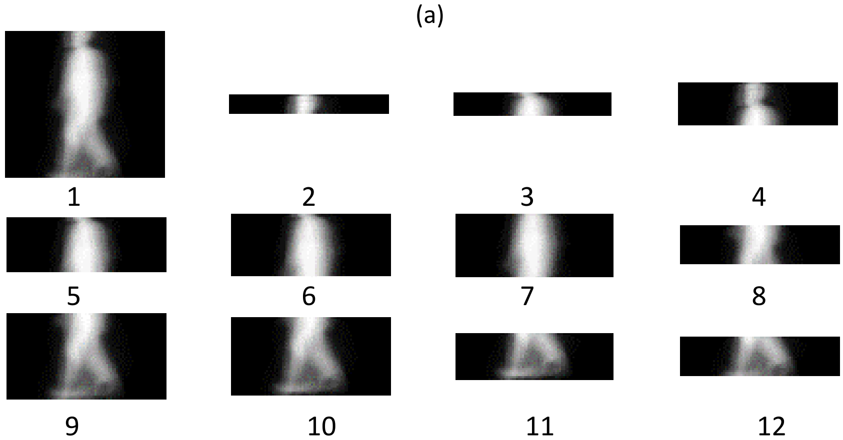
This research uses the average anthropometric measurement as it can be seen in Figure 5.2(a) [48]. Twelve different human body parts based on body height (H) are selected for this study. The start and end points of each part are shown in Table 5.1 and the example GEI of each part is shown in Figure 5.2(b).

Table 5-1: Range of each partial silhouette

Part	Start	End	Note
1	1	H	full body
2	1	0.13*H	head
3	0.13*H	0.28*H	chin to chest
4	1	0.28*H	head to chest
5	0.13*H	0.47*H	chin to waist
6	0.13*H	0.515*H	chin to hip
7	0.13*H	0.623*H	chin to finger
8	0.47*H	0.715*H	thigh
9	0.47*H	H	limb
10	0.515*H	H	lower hip
11	0.715*H	H	lower knee
12	0.715*H	0.961*H	ankle



(a)



(b)

Figure 5-2: Anthropometric Measurement and Different Partial Silhouette

5.1.2 Evaluation

In this section, each body part was tested with the general gait recognition system in Figure 5.2. The personal model was trained by four normal walking datasets, and testing was conducted by two datasets from each appearance. Four gait representations including GEI, CGI-D-1, GHGI and CGHCI were used in this experiment. CGI was obtained with filter size 3x3x1x16 as a convolutional parameter. GHGI used cell size 2x2, block size 2x2 and 18 orientation histogram bins which were the optimized HOG parameters for all parts. CGHGI used the same HOG parameter for generating GHGI and filter size 3x3x18x36 in convolutional operations. The detailed recognition result for each view angle is shown in Tables 5.2 to 5.5.

GEI representation part 11 or lower knee had the best average classification rate of 82.16% in case of mixed appearances as show in Table 5.2. If each appearance was separately considered, the best average classification rate of normal walking, walking with a bag and walking with coat were in order 99.13%-part 1, 78.68%-part 4 and 81.03%-part 11. If each view angle was separately considered, the best average classification rate of normal walking, walking with a bag, walking with a coat and mixed appearances were in order 100%-18° part 1 and 6, 86.64%-108° part 4, 87.33%-54° part 11 and 85.20%-90° part 2, respectively.

CGI representation part 11 or lower knee had the best average classification rate of 84.15% in case of mixed appearances as it is shown in Table 5.3. If each appearance was separately considered, the best average normal walking, walking with a bag and walking with a coat were in order 99.18%-part 1, 79.66%-part 4 and 84.20%-part 11. If each view angle was separately considered, the best average normal walking, walking with a bag, walking with a coat and mixed appearances were 100%-18° part 1 and 7, 83.79%-108° part 4, 87.50%-54° part 11 and 86.21%-108° part 11, respectively.

Table 5-2: GEI single part

Part	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	**99.57**	**100**	**99.57**	98.71	**98.71**	**99.14**	**99.14**	**99.14**	98.62	98.71	**99.14**	**99.13**
	Bag	**75.26**	71.38	71.72	65.43	67.07	65.69	68.53	69.22	69.05	71.81	**78.19**	70.31
	Coat	46.98	57.67	55.26	59.48	57.50	57.33	54.74	53.19	51.90	51.12	47.93	53.92
	Mixed	73.94	76.35	75.52	74.54	74.43	74.05	74.14	73.85	73.19	73.88	75.09	74.45
2	Normal	98.45	97.76	96.03	97.33	96.81	96.72	96.47	94.57	97.41	95.78	96.98	96.76
	Bag	62.24	68.97	73.10	66.38	78.62	78.53	75.00	71.81	66.72	68.19	65.09	70.42
	Coat	80.34	73.10	76.21	74.31	79.91	**80.34**	**78.53**	74.74	76.72	71.47	74.14	76.35
	Mixed	80.34	79.94	**81.78**	79.34	**85.11**	**85.20**	**83.33**	80.37	**80.29**	78.48	78.74	81.18
3	Normal	97.41	97.59	98.45	97.67	97.50	96.55	97.41	96.98	96.98	98.28	97.33	97.47
	Bag	59.91	68.71	73.10	69.74	74.22	77.67	79.31	71.12	74.31	70.00	68.71	71.53
	Coat	18.28	23.19	34.74	30.95	36.64	33.97	34.31	29.14	31.38	20.34	16.12	28.10
	Mixed	58.53	63.16	68.76	66.12	69.45	69.40	70.34	65.75	67.56	62.87	60.72	65.70
4	Normal	99.14	99.48	99.31	99.14	98.36	97.93	98.45	97.41	97.50	98.02	98.28	98.46
	Bag	67.84	**77.50**	**79.66**	**77.41**	**81.72**	**85.09**	**86.64**	**83.28**	**75.43**	**77.33**	73.62	**78.68**
	Coat	34.48	45.43	43.28	47.16	49.31	44.14	41.98	41.47	45.34	29.66	35.00	41.57
	Mixed	67.16	74.14	74.08	74.57	76.47	75.72	75.69	74.05	72.76	68.33	68.97	72.90
5	Normal	68.53	71.55	71.12	66.81	67.67	65.09	68.10	68.10	72.84	72.41	75.00	69.75
	Bag	67.84	71.72	71.64	66.38	68.36	65.09	67.76	68.19	72.76	72.24	74.91	69.72
	Coat	15.86	24.91	34.48	37.33	35.26	33.79	34.05	30.52	29.66	24.22	16.98	28.82
	Mixed	50.75	56.06	59.08	56.84	57.10	54.66	56.64	55.60	58.42	56.29	55.63	56.10
6	Normal	99.48	**100**	98.53	98.28	98.28	97.84	97.50	97.41	97.84	97.50	97.93	98.24
	Bag	69.05	68.36	64.83	57.59	57.67	55.52	57.07	62.33	66.38	68.02	72.84	63.61
	Coat	18.28	25.17	31.72	35.95	32.84	30.43	28.45	27.07	29.74	22.50	13.88	26.91
	Mixed	62.27	64.51	65.03	63.94	62.93	61.26	61.01	62.27	64.66	62.67	61.55	62.92
7	Normal	99.57	99.57	98.79	98.02	98.28	98.28	98.28	97.84	98.71	97.84	98.88	98.55
	Bag	67.93	60.52	55.60	53.02	47.67	40.95	49.14	53.02	53.53	58.45	64.91	54.98
	Coat	24.83	32.59	35.95	38.53	34.57	30.09	30.34	32.67	32.76	32.41	24.14	31.72
	Mixed	64.11	64.22	63.45	63.19	60.17	56.44	59.25	61.18	61.67	62.90	62.64	61.75
8	Normal	97.50	98.71	97.76	**99.31**	98.28	98.28	**99.14**	98.36	98.28	97.41	97.84	98.26
	Bag	42.50	42.07	37.16	28.45	28.62	25.43	34.22	33.02	32.16	34.40	37.33	34.12
	Coat	29.91	39.66	43.45	39.91	35.86	37.50	31.90	26.98	33.28	30.78	26.47	34.15
	Mixed	56.64	60.14	59.45	55.89	54.25	53.74	55.09	52.79	54.57	54.20	53.88	55.51
9	Normal	99.14	99.57	97.76	99.22	**98.71**	99.14	98.71	**99.14**	**99.14**	**99.14**	98.71	98.94
	Bag	63.62	55.52	51.47	45.26	43.02	40.26	45.26	48.28	44.57	52.16	55.43	49.53
	Coat	52.07	65.00	62.84	64.05	60.52	60.26	58.53	54.48	51.81	53.45	53.36	57.85
	Mixed	71.61	73.36	70.69	69.51	67.41	66.55	67.50	67.30	65.17	68.25	69.17	68.77
10	Normal	98.71	98.28	96.81	98.71	**98.71**	98.71	98.28	98.71	98.28	98.71	98.71	98.42
	Bag	60.52	55.86	51.29	46.21	42.93	42.67	46.90	45.95	43.62	50.95	50.86	48.89
	Coat	60.00	68.53	65.95	67.24	64.05	61.47	59.74	59.83	56.55	59.91	62.24	62.32
	Mixed	73.07	74.22	71.35	70.72	68.56	67.61	68.30	68.16	66.15	69.86	70.60	69.87
11	Normal	98.53	97.84	96.98	98.36	98.19	98.97	97.67	97.50	97.41	96.47	97.84	97.80
	Bag	66.55	68.28	61.55	66.55	70.95	70.60	71.03	68.10	64.05	66.47	70.09	67.66
	Coat	**81.98**	**85.09**	**85.26**	**87.33**	**81.47**	79.31	77.59	**78.71**	**78.02**	**79.05**	**77.50**	**81.03**
	Mixed	**82.36**	**83.74**	81.26	**84.08**	83.53	82.96	82.10	**81.44**	79.83	**80.66**	**81.81**	**82.16**
12	Normal	97.33	98.02	96.90	97.67	98.28	**99.14**	98.10	98.28	97.41	96.38	97.41	97.72
	Bag	64.14	63.97	58.19	63.62	68.88	69.74	68.28	65.60	60.34	63.10	65.09	64.63
	Coat	80.09	82.59	83.36	84.48	80.34	79.48	77.07	78.19	77.76	74.91	76.55	79.53
	Mixed	80.52	81.52	79.48	81.93	82.50	82.79	81.15	80.69	78.51	78.13	79.68	80.63

Table 5-3: CGI Single Part

Part	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	99.57	**100**	**99.74**	**99.14**	**98.62**	**98.45**	**98.62**	**98.88**	**99.05**	**99.31**	**99.57**	**99.18**
	Bag	**80.43**	**79.74**	**78.97**	75.09	79.14	80.17	82.33	81.03	**77.59**	**80.17**	**81.64**	**79.66**
	Coat	50.52	66.12	63.97	69.74	72.67	72.93	72.67	65.17	63.88	58.71	51.90	64.39
	Mixed	76.84	81.95	80.89	81.32	83.48	83.85	84.54	81.70	80.17	79.40	77.70	81.08
2	Normal	96.72	96.64	94.40	94.31	92.76	90.17	92.33	91.64	93.45	94.14	95.17	93.79
	Bag	59.57	66.38	65.26	63.45	67.24	71.55	68.71	63.45	63.28	62.67	63.97	65.05
	Coat	80.17	80.43	79.48	77.24	78.45	80.86	79.66	76.72	76.64	73.10	76.29	78.10
	Mixed	78.82	81.15	79.71	78.33	79.48	80.86	80.23	77.27	77.79	76.64	78.48	78.98
3	Normal	98.53	98.53	96.98	97.24	95.95	96.29	96.47	97.16	97.07	97.50	97.93	97.24
	Bag	64.31	66.12	69.14	70.34	72.33	75.26	79.91	76.72	68.53	66.64	65.43	70.43
	Coat	18.36	22.33	33.19	39.22	44.91	44.40	41.64	35.78	31.64	23.79	18.45	32.16
	Mixed	60.40	62.33	66.44	68.94	71.06	71.98	72.67	69.89	65.75	62.64	60.60	66.61
4	Normal	99.05	98.97	98.28	98.10	96.98	96.98	97.33	97.16	96.55	97.50	98.19	97.74
	Bag	69.48	74.66	76.81	**76.55**	**80.43**	**83.53**	**83.79**	**81.12**	73.97	74.57	70.86	76.89
	Coat	35.00	44.66	49.22	57.59	58.97	61.12	57.50	52.07	49.83	38.62	36.12	49.15
	Mixed	67.84	72.76	74.77	77.41	78.79	80.55	79.54	76.78	73.45	70.23	68.39	74.59
5	Normal	66.38	68.10	70.69	65.09	65.09	64.66	68.10	68.97	64.66	69.40	66.81	67.08
	Bag	70.09	72.33	78.53	72.24	73.02	71.12	77.07	76.12	76.47	75.09	73.02	74.10
	Coat	17.59	28.45	38.71	43.79	47.67	47.50	45.52	40.95	39.66	28.79	16.81	35.95
	Mixed	51.35	56.29	62.64	60.37	61.93	61.09	63.56	62.01	60.26	57.76	52.21	59.04
6	Normal	99.66	99.74	98.88	98.28	97.33	96.98	97.50	97.67	97.24	98.02	99.05	98.21
	Bag	70.95	71.98	73.45	68.62	70.52	68.71	73.28	73.79	74.91	74.14	72.59	72.08
	Coat	19.22	27.67	38.02	43.88	45.34	45.26	44.74	39.66	37.50	27.84	17.59	35.16
	Mixed	63.28	66.47	70.11	70.26	71.06	70.32	71.84	70.37	69.89	66.67	63.07	68.48
7	Normal	**99.66**	**100**	99.40	98.53	98.10	97.50	98.10	98.79	98.19	98.53	99.57	98.76
	Bag	70.86	70.43	66.72	63.71	61.29	62.41	66.21	65.09	68.45	71.12	71.03	67.03
	Coat	25.34	34.14	41.98	48.36	46.38	45.09	42.33	40.78	40.17	33.19	23.28	38.28
	Mixed	65.29	68.19	69.37	70.20	68.59	68.33	68.88	68.22	68.94	67.61	64.63	68.02
8	Normal	97.76	99.40	98.45	98.88	98.36	96.64	97.24	98.10	98.62	98.88	98.88	98.29
	Bag	46.98	48.02	42.59	37.50	36.98	36.64	40.95	42.59	39.57	44.14	43.19	41.74
	Coat	35.86	47.33	50.86	51.38	47.67	48.19	46.38	41.38	45.78	43.53	36.03	44.95
	Mixed	60.20	64.91	63.97	62.59	61.01	60.49	61.52	60.69	61.32	62.18	59.37	61.66
9	Normal	98.71	99.40	98.53	98.71	98.10	97.93	97.33	97.24	98.28	98.53	98.97	98.34
	Bag	68.19	60.95	54.57	56.03	56.55	58.53	66.03	60.78	55.78	58.71	62.24	59.85
	Coat	60.69	70.95	70.17	74.05	72.67	72.24	69.48	66.47	66.38	64.48	62.59	68.20
	Mixed	75.86	77.10	74.43	76.26	75.78	76.24	77.61	74.83	73.48	73.91	74.60	75.46
10	Normal	98.62	99.05	97.93	98.71	97.76	97.24	96.64	96.90	98.02	98.28	98.88	98.00
	Bag	65.09	61.72	56.72	56.98	58.97	59.91	66.29	61.72	55.43	57.76	61.03	60.15
	Coat	68.97	74.05	73.88	77.76	76.29	73.45	70.95	71.38	69.66	70.43	70.69	72.50
	Mixed	77.56	78.28	76.18	77.82	77.67	76.87	77.96	76.67	74.37	75.49	76.87	76.88
11	Normal	98.71	97.93	96.98	96.90	96.72	96.03	95.26	95.00	95.17	96.29	97.76	96.61
	Bag	70.09	67.07	64.40	69.31	76.55	78.79	79.91	73.97	68.36	67.76	71.72	71.63
	Coat	**84.14**	**85.86**	**86.38**	**87.50**	**84.40**	**83.45**	**83.45**	**83.10**	**83.45**	**81.03**	**83.45**	**84.20**
	Mixed	**84.31**	**83.62**	**82.59**	**84.57**	**85.89**	**86.09**	**86.21**	**84.02**	**82.33**	**81.70**	**84.31**	**84.15**
12	Normal	98.45	97.41	96.64	97.07	96.21	96.38	95.52	95.00	95.17	96.29	97.41	96.50
	Bag	67.33	63.71	59.48	66.29	72.93	77.67	76.47	71.98	65.86	64.74	69.22	68.70
	Coat	82.50	84.83	84.91	86.29	83.28	82.07	82.76	82.76	82.16	78.71	82.07	82.94
	Mixed	82.76	81.98	80.34	83.22	84.14	85.37	84.91	83.25	81.06	79.91	82.90	82.71

Table 5-4: GHGI single Part

Part	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	96.12	**100**	99.14	**99.14**	98.71	**98.71**	**99.14**	**99.14**	98.71	**99.57**	97.84	**98.75**
	Bag	**85.78**	90.09	**91.81**	**93.53**	**95.69**	95.69	**95.26**	**92.67**	89.22	89.22	**86.21**	**91.38**
	Coat	**88.79**	**93.10**	92.67	**90.95**	**87.93**	**87.93**	**86.21**	**84.05**	86.64	84.91	82.76	**87.81**
	Average	**90.23**	**94.40**	**94.54**	**94.54**	**94.11**	**94.11**	**93.53**	**91.95**	**91.52**	**91.24**	**88.94**	**92.65**
2	Normal	95.26	97.84	96.55	97.41	95.26	96.98	96.55	95.69	93.53	96.12	95.69	96.08
	Bag	75.00	81.47	81.03	83.62	86.21	90.95	87.50	88.79	86.21	85.34	80.17	84.21
	Coat	81.03	72.41	77.59	75.86	83.19	81.90	80.60	77.16	75.43	74.57	75.86	77.78
	Average	83.76	83.91	85.06	85.63	88.22	89.94	88.22	87.21	85.06	85.34	83.91	86.02
3	Normal	95.69	98.71	97.41	97.41	96.55	96.98	96.12	96.55	97.41	96.98	97.41	97.02
	Bag	82.33	82.76	84.48	85.78	84.48	90.52	88.36	85.78	86.64	88.36	81.03	85.50
	Coat	62.07	59.91	54.74	55.17	48.28	50.00	47.41	51.72	54.74	50.00	56.47	53.68
	Average	80.03	80.46	78.88	79.45	76.44	79.17	77.30	78.02	79.60	78.45	78.30	78.74
4	Normal	**97.41**	98.71	98.28	97.41	97.84	96.55	97.41	96.12	97.41	97.84	97.84	97.53
	Bag	82.33	**90.52**	90.09	91.38	93.10	**96.12**	93.10	91.38	**90.52**	**90.09**	85.78	90.40
	Coat	77.59	74.57	73.28	76.72	78.02	72.84	71.98	74.14	73.28	71.12	71.98	74.14
	Average	85.78	87.93	87.21	88.51	89.66	88.51	87.50	87.21	87.07	86.35	85.20	87.36
5	Normal	95.26	98.28	98.71	97.84	98.71	96.55	97.84	97.84	97.84	97.41	96.55	97.53
	Bag	83.19	87.93	86.64	83.62	86.21	87.07	86.21	89.22	88.36	87.50	83.19	86.29
	Coat	65.09	71.55	64.66	62.50	64.22	60.78	59.05	61.21	62.93	60.78	59.05	62.89
	Average	81.18	85.92	83.33	81.32	83.05	81.47	81.03	82.76	83.05	81.90	79.60	82.24
6	Normal	95.26	98.28	**99.57**	98.28	98.71	96.55	97.84	98.28	98.28	97.84	96.55	97.77
	Bag	85.34	89.22	86.21	83.62	87.93	88.79	87.50	90.09	89.22	86.64	83.62	87.11
	Coat	66.81	71.98	68.53	66.38	65.95	62.50	61.21	62.93	62.50	60.34	59.48	64.42
	Average	82.47	86.49	84.77	82.76	84.20	82.61	82.18	83.76	83.33	81.61	79.89	83.10
7	Normal	95.69	98.71	**99.57**	**99.14**	98.28	**98.71**	98.28	98.28	**99.14**	97.84	96.55	98.20
	Bag	**85.78**	88.36	85.34	86.21	85.78	86.64	87.50	86.64	86.64	87.07	82.33	86.21
	Coat	74.14	78.88	74.57	73.71	71.55	65.09	66.81	67.67	69.83	68.53	65.52	70.57
	Average	85.20	88.65	86.49	86.35	85.20	83.48	84.20	84.20	85.20	84.48	81.47	84.99
8	Normal	95.26	97.84	98.71	98.71	98.28	98.28	97.84	97.41	97.84	98.28	**98.28**	97.88
	Bag	77.59	75.00	75.00	74.14	70.69	72.41	73.71	71.55	72.84	72.84	72.41	73.47
	Coat	80.60	84.48	80.17	79.74	75.00	69.40	70.26	71.98	75.86	79.31	75.43	76.57
	Average	84.48	85.78	84.63	84.20	81.32	80.03	80.60	80.32	82.18	83.48	82.04	82.64
9	Normal	93.97	96.98	97.41	**99.14**	**99.14**	**98.71**	98.28	98.28	98.28	98.28	96.12	97.69
	Bag	78.88	80.17	84.48	90.52	93.10	90.95	89.66	85.34	81.47	81.90	78.88	85.03
	Coat	**88.79**	91.81	**93.97**	**90.95**	87.07	85.34	83.19	**84.05**	86.64	86.64	**85.78**	87.66
	Average	87.21	89.66	91.95	93.53	93.10	91.67	90.37	89.22	88.79	88.94	86.93	90.13
10	Normal	93.53	96.55	96.98	98.71	98.28	98.28	97.84	97.41	97.41	97.84	95.26	97.10
	Bag	76.29	77.16	84.05	87.93	92.67	90.52	89.66	85.78	81.47	78.02	80.60	84.01
	Coat	**88.79**	90.52	92.24	90.52	87.50	86.64	84.05	83.62	**87.07**	**88.79**	**85.78**	87.77
	Average	86.21	88.07	91.09	92.39	92.82	91.81	90.52	88.94	88.65	88.22	87.21	89.63
11	Normal	93.10	95.26	95.69	98.71	98.28	96.55	96.55	95.26	93.53	93.53	93.97	95.49
	Bag	71.98	75.43	80.60	90.09	93.53	92.67	90.09	84.48	81.90	73.71	78.88	83.03
	Coat	86.64	90.09	90.95	89.22	86.21	85.78	82.76	81.90	84.91	83.62	83.62	85.97
	Average	83.91	86.93	89.08	92.67	92.67	91.67	89.80	87.21	86.78	83.62	85.49	88.17
12	Normal	91.81	94.83	96.12	97.84	97.41	96.98	96.55	94.83	93.97	93.10	93.53	95.18
	Bag	70.69	74.57	78.02	88.79	93.53	91.81	89.22	84.48	81.90	74.57	78.45	82.37
	Coat	86.64	89.22	88.79	87.07	84.91	86.64	81.90	79.31	82.76	81.47	83.19	84.72
	Average	83.05	86.21	87.64	91.24	91.95	91.81	89.22	86.21	86.21	83.05	85.06	87.42

Table 5-5: CGHGI Single Part

Part	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	96.12	**100**	**99.48**	**99.14**	98.71	**98.79**	**98.97**	**99.14**	98.62	**99.48**	98.02	**98.77**
	Bag	85.43	**90.34**	**92.50**	**93.71**	**96.03**	**95.78**	**95.00**	**93.02**	88.97	**88.88**	85.86	**91.41**
	Coat	88.88	**92.24**	**93.19**	90.43	**87.93**	**88.10**	**85.86**	**84.83**	**86.98**	85.26	83.62	**87.94**
	Average	**90.14**	**94.20**	**95.06**	**94.43**	**94.22**	**94.22**	**93.28**	**92.33**	**91.52**	**91.21**	**89.17**	**92.71**
2	Normal	95.34	97.76	96.47	97.16	95.52	96.21	96.64	94.66	93.71	95.60	95.17	95.84
	Bag	75.26	81.47	81.03	83.79	85.34	90.26	86.98	87.24	84.40	85.26	79.83	83.71
	Coat	81.12	72.16	76.81	74.57	83.53	82.59	80.78	76.64	75.86	74.66	75.00	77.61
	Average	83.91	83.79	84.77	85.17	88.13	89.68	88.13	86.18	84.66	85.17	83.33	85.72
3	Normal	96.47	98.62	97.59	97.41	96.55	96.55	96.29	96.72	97.50	97.07	97.33	97.10
	Bag	81.98	83.19	85.26	84.14	84.83	88.53	87.93	86.38	86.38	87.07	81.38	85.19
	Coat	60.17	59.91	53.79	54.14	46.90	50.43	48.71	51.03	54.31	50.69	55.09	53.20
	Average	79.54	80.57	78.88	78.56	76.09	78.51	77.64	78.05	79.40	78.28	77.93	78.50
4	Normal	**97.33**	98.71	98.10	97.67	98.36	97.07	97.24	96.38	97.16	97.59	97.59	97.56
	Bag	83.45	89.66	89.57	90.69	92.59	95.60	92.50	91.12	**90.00**	**88.88**	**86.72**	90.07
	Coat	77.84	74.83	72.59	76.72	77.76	73.36	73.19	75.52	74.83	71.03	71.90	74.51
	Average	86.21	87.73	86.75	88.36	89.57	88.68	87.64	87.67	87.33	85.83	85.40	87.38
5	Normal	95.26	98.10	98.71	97.84	98.36	96.72	97.76	98.02	97.76	97.76	96.29	97.51
	Bag	83.19	87.67	85.78	84.31	86.21	87.67	88.88	89.48	88.02	87.07	83.02	86.48
	Coat	64.91	69.91	63.88	61.81	63.45	59.48	58.45	60.26	63.19	60.43	58.79	62.23
	Average	81.12	85.23	82.79	81.32	82.67	81.29	81.70	82.59	82.99	81.75	79.37	82.07
6	Normal	95.26	98.45	99.31	98.28	98.53	96.55	97.93	98.10	98.28	97.93	96.55	97.74
	Bag	85.17	88.97	85.43	84.40	86.64	88.45	88.10	89.66	88.71	87.24	83.10	86.90
	Coat	66.03	71.90	68.88	67.59	65.17	62.59	61.21	62.16	63.36	61.03	58.62	64.41
	Average	82.16	86.44	84.54	83.42	83.45	82.53	82.41	83.30	83.45	82.07	79.43	83.02
7	Normal	95.69	98.71	**99.48**	99.05	98.36	98.62	98.28	98.28	**98.97**	98.45	96.98	98.26
	Bag	**85.78**	87.76	86.03	86.03	85.78	85.95	86.98	87.41	86.03	86.21	82.07	86.00
	Coat	73.10	78.88	73.71	74.48	70.52	65.17	67.76	67.33	69.74	67.84	66.12	70.42
	Average	84.86	88.45	86.41	86.52	84.89	83.25	84.34	84.34	84.91	84.17	81.72	84.90
8	Normal	95.17	98.02	98.71	98.71	98.19	97.93	97.67	97.33	98.19	98.53	**98.19**	97.88
	Bag	75.78	74.48	73.97	73.97	69.83	71.29	71.47	71.21	70.52	71.47	72.24	72.38
	Coat	79.14	82.84	81.72	79.22	74.57	70.34	69.05	71.98	76.55	77.67	75.60	76.25
	Average	83.36	85.11	84.80	83.97	80.86	79.86	79.40	80.17	81.75	82.56	82.01	82.17
9	Normal	93.97	96.98	97.67	**99.14**	**98.97**	98.71	98.28	98.28	98.28	98.36	96.12	97.70
	Bag	77.41	79.05	83.79	88.79	91.81	90.60	89.48	85.52	81.55	80.78	79.05	84.35
	Coat	88.88	91.21	**93.19**	**91.12**	87.16	85.69	83.79	84.14	86.21	86.98	85.52	87.63
	Average	86.75	89.08	91.55	93.02	92.64	91.67	90.52	89.31	88.68	88.71	86.90	89.89
10	Normal	93.53	96.21	96.98	98.79	98.36	98.19	97.84	97.41	97.59	97.93	95.09	97.08
	Bag	75.52	76.12	84.31	87.93	91.90	89.40	88.02	85.34	81.12	77.67	80.26	83.42
	Coat	**88.97**	89.91	93.02	90.78	87.84	86.81	83.36	83.97	85.95	**87.33**	**86.29**	87.66
	Average	86.01	87.41	91.44	92.50	92.70	91.47	89.74	88.91	88.22	87.64	87.21	89.39
11	Normal	92.76	95.26	96.38	98.62	98.10	96.98	96.21	95.43	93.62	93.88	93.88	95.56
	Bag	70.69	74.14	79.31	89.14	93.97	93.02	89.22	84.31	80.52	73.36	79.83	82.50
	Coat	86.90	88.97	90.86	90.00	86.03	86.47	82.59	81.90	84.40	83.62	82.84	85.87
	Average	83.45	86.12	88.85	92.59	92.70	92.16	89.34	87.21	86.18	83.62	85.52	87.98
12	Normal	91.72	94.83	96.21	98.02	97.41	96.55	96.55	94.83	93.10	93.36	93.36	95.09
	Bag	70.60	73.62	78.02	87.33	93.79	92.84	88.62	84.31	80.43	73.19	79.40	82.01
	Coat	87.16	88.88	89.40	88.10	84.40	86.90	81.55	79.83	83.19	80.78	83.79	84.91
	Average	83.16	85.78	87.87	91.15	91.87	92.10	88.91	86.32	85.57	82.44	85.52	87.34

GHGI representation part 1 or full body had the best average classification rate of 92.65% in case of mixed appearances as it is shown in Table 5.4. If each appearance was separately considered, the best average normal walking, walking with a bag and walking with a coat were in order 98.75%-part 1, 91.38%-part 1 and 87.81%-part 1. If each view angle was separately considered, the best average normal walking, walking with a bag, walking with a coat and mixed appearances were 100%-18° part 1, 96.12%-90° part 4, 93.97%-36° part 9 and 94.54%-36° part 1 and 54° part 1, respectively.

CGHGI representation part 1 or full body had the best average classification rate of 92.71% in case of mixed appearances as it is shown in Table 5.5. If each appearance was separately considered, the best average normal walking, walking with a bag and walking with a coat were in order 98.77%-part 1, 91.41%-part 1 and 87.94%-part 1. If each view angle was separately considered, the best average normal walking, walking with a bag, walking with a coat and mixed appearances were 100%-18° part 1, 96.03%-72° part 1, 93.19%-36° part 1 and 95.06%-36° part 1, respectively.

5.1.3 Discussion

Taking appearance and gait representation into account, the average classification rates are shown in Table 5.6. This classification rate is averaged over eleven view angle. The best average classification rate in case of normal walking, walking with a bag, walking with a coat, and mixed appearance is 99.18% CGI part 1, 91.41%-CGHGI part 1, 87.94%-CGHGI part 1 and 92.71%-CGHGI part 1, respectively. Part 1 or full body has the highest classification rate for all appearances in various representations. Part 11 or lower knee has the highest classification rate of 82.16%-GEI and 84.15%-CGI. It has been noticed that part 1 GHGI has the highest classification rate of 92.65% when is tested with mixed appearance dataset. GHGI in Chapter 4 has the highest classification rate of 93.13% as it can be seen in Table 4.18. Chapter 4 focuses on full body gait recognition which chooses a cell size of 2x2, block size 3x3 and 15 orientation histogram bins as HOG parameters when training a personal model with four normal walking datasets. Chapter 5 uses the same HOG parameters for all parts. The optimized HOG parameters set as cell size 2x2, block size 2x2 and 18 orientation histogram bins.

The best four parts for gait representations were

- GEI: 82.16% part 11, 81.18% part 2, 80.63% part 12 and 74.45% part 1
- CGI: 84.15% part 11, 82.71% part 12, 81.08% part 1 and 78.98% part 2
- GHGI: 92.65% part 1, 90.13% part 9, 89.63% part 10 and 88.17% part 11
- CGHGI: 92.71% part 1, 89.89% part 9, 89.39% part 10 and 87.98% part 11

Table 5-6: Summarized Single Part Classification Rates

Part	Appearance	GEI	CGI	GHGI	CGHGI	Part	Appearance	GEI	CGI	GHGI	CGHGI
1	Normal	**99.13**	**99.18**	**98.75**	**98.77**	7	Normal	98.55	98.76	98.20	98.26
	Bag	70.31	**79.66**	**91.38**	**91.41**		Bag	54.98	67.03	86.21	86.00
	Coat	53.92	64.39	**87.81**	**87.94**		Coat	31.72	38.28	70.57	70.42
	Mixed	74.45	81.08	**92.65**	**92.71**		Mixed	61.75	68.02	84.99	84.90
2	Normal	96.76	93.79	96.08	95.84	8	Normal	98.26	98.29	97.88	97.88
	Bag	70.42	65.05	84.21	83.71		Bag	34.12	41.74	73.47	72.38
	Coat	76.35	78.10	77.78	77.61		Coat	34.15	44.95	76.57	76.25
	Mixed	81.18	78.98	86.02	85.72		Mixed	55.51	61.66	82.64	82.17
3	Normal	97.47	97.24	97.02	97.10	9	Normal	98.94	98.34	97.69	97.70
	Bag	71.53	70.43	85.50	85.19		Bag	49.53	59.85	85.03	84.35
	Coat	28.10	32.16	53.68	53.20		Coat	57.85	68.20	87.66	87.63
	Mixed	65.70	66.61	78.74	78.50		Mixed	68.77	75.46	90.13	89.89
4	Normal	98.46	97.74	97.53	97.56	10	Normal	98.42	98.00	97.10	97.08
	Bag	**78.68**	76.89	90.40	90.07		Bag	48.89	60.15	84.01	83.42
	Coat	41.57	49.15	74.14	74.51		Coat	62.32	72.50	87.77	87.66
	Mixed	72.90	74.59	87.36	87.38		Mixed	69.87	76.88	89.63	89.39
5	Normal	69.75	67.08	97.53	97.51	11	Normal	97.80	96.61	95.49	95.56
	Bag	69.72	74.10	86.29	86.48		Bag	67.66	71.63	83.03	82.50
	Coat	28.82	35.95	62.89	62.23		Coat	**81.03**	**84.20**	85.97	85.87
	Mixed	56.10	59.04	82.24	82.07		Mixed	**82.16**	**84.15**	88.17	87.98
6	Normal	98.24	98.21	97.77	97.74	12	Normal	97.72	96.50	95.18	95.09
	Bag	63.61	72.08	87.11	86.90		Bag	64.63	68.70	82.37	82.01
	Coat	26.91	35.16	64.42	64.41		Coat	79.53	82.94	84.72	84.91
	Mixed	62.92	68.48	83.10	83.02		Mixed	80.63	82.71	87.42	87.34

Part 11 (lower knee) and part 12 (ankle) have a better classification rate than part 1 or full body in case of GEI and CGI. Both parts have a much higher classification rate than that of part 1 when tested by walking with a coat dataset. In case of HOG representation, part 1 has enormously improved their classification rate when tested by walking with a bag and a coat dataset. Nonetheless, part 9 which has the second highest classification rate has its' classification rate approximately 2-3% less than that of full body. This means that other body parts may be better than full body in gait recognition.

Taking all representations into account, there are seven parts by which their averaged classification rate is of a higher score than 80%. These parts include part 11 85.61%, part 2 85.22%, part 12 84.52%, part 2 82.97%, part 10 81.44%, part 9 81.06% and part 4 80.56%. These seven parts are further studied in the following sections.

5.2 Part Score Fusion (PSF)

Experiments in Section 5.1 test individual part gait recognition while the experiment in this section is to test gait recognition from parts fusion. Two selected parts are separately trained for two personal models as they are shown in Figure 5.3. When a probe sample is tested, each selected part is compared with the relevant personal model. The final score for each person is the mean scores of the two parts. The highest score is chosen as the prediction of the recognized person.

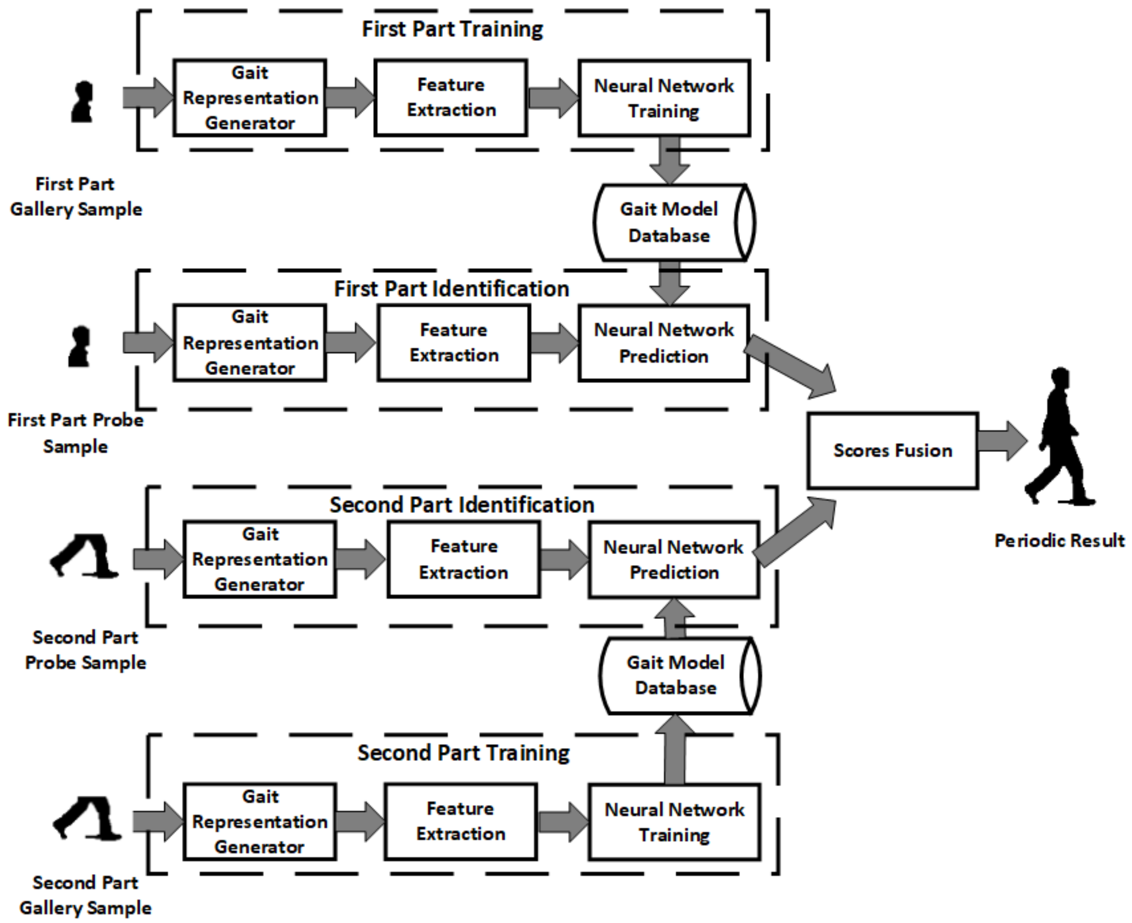


Figure 5-3: Score fusion gait identification system

5.2.1 Part Selection Criteria

There are seven parts included, 1, 2, 4, 9, 10, 11 and 12 are selected for parts fusion experiment. These parts have higher than eighty percent correct classification accuracy when the classification rate in Table 5.6 is averaged from all gait representation. Two parts are selected to make one fusion. There are two strategies for part selection.

- First strategy: the full body is fused with another part as it is normally used in gait recognition. Thus the first part is set as the main part and fuses with another selected part. There are six fusions under this strategy.
- Second strategy: the remaining parts are separated into the upper body (head to chest) and the lower body (under the waist). Part 2 and 4 are the upper body parts. One upper body part and one lower body part are fused for training and testing. There are eight fusions.

Overall, there are fourteen fusions as shown in Table 5.7

Table 5-7: Partial silhouette fusion

Fusion	First part	Second part
1	1	2
2	1	4
3	1	9
4	1	10
5	1	11
6	1	12
7	2	9
8	2	10
9	2	11
10	2	12
11	4	9
12	4	10
13	4	11
14	4	12

5.2.2 Evaluation

In this section, each fusion created two gait models per person, they were individually trained by a selected part in Table 5.7. In testing, the final personal score was calculated from both models by add operation. The highest score was chosen as the SVM prediction result. Detailed scores of each gait representation are shown in Tables 5.8 – 5.11. All experiments in this section used four normal walking datasets in the training phase.

GEI had the best classification rate of 85.72% for the mixed appearance at fusion 5 in Table 5.8, in which part 2 (head) is fused with part 11 (lower knee). This rate increased by approximately 3% compared with GEI part 11 in Table 5.2. The best view angle was 90° with the rate of 88.51% at fusion 9. The best classification rate in the case of normal walking, walking with a bag and walking witha coat testing was 99.37% at fusion 1, 79.98% at fusion 2 and 83.46% at fusion 9, respectively. Almost all fusions had a better classification rate than the individual part does except fusions 3, 7 and 8.

Part score fusion CGI had the best classification rate of 86.56% fusion 9 which fused part 1 (head) and part 11 (lower knee) when four normal walking datasets were used in training phase as it is shown in Table 5.9. This rate increased by approximately 2% compared with CGI part 11 in Table 5.3. The best view angle was 90° with rate 89.13% fusion 9 when was tested by mixed appearance dataset. Best classification rate in the case of normal walking, walking with a bag and a coat testing was 98.93% fusion 11, 79.51% fusion 2 and 86.17% fusion 9, respectively. Almost every fusion had a better classification rate than the individual part does except fusions 2, 3 and 4.

Part score fusion GHGI had the best classification rate of 92.84% fusion 12 which fused part 4 (head to chest) and part 10 (lower hip) when four normal walking datasets were used in training phase as it is shown in Table 5.10. This rate slightly increased when compared with GHGI part 1 in Table 5.4. The best view angle was 72° with rate 95.55% fusion 12 when was tested by mixed appearance dataset. Best classification rate in case of normal walking, walking with a bag and a coat testing was 98.47% fusion 3, 92.24% fusion 2 and 89.26% fusion 5, respectively. Fusion 1-6 had a lower classification rate than individual part 1 while the remaining had a higher rate than individual selected parts.

Table 5-8: GEI part score fusion

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	**99.57**	**100**	**99.57**	**99.57**	**99.14**	99.14	**99.14**	98.71	**99.57**	98.71	**100**	**99.37**
	Bag	77.59	77.59	79.31	75.43	**82.76**	81.47	80.17	78.88	73.71	76.29	76.72	78.17
	Coat	74.14	75.00	75.43	69.83	75.43	78.02	74.57	67.67	75.00	71.12	69.40	73.24
	Mixed	83.76	84.20	84.77	81.61	85.78	86.21	84.63	81.75	82.76	82.04	82.04	83.59
2	Normal	**99.57**	**100**	**99.57**	**99.57**	98.71	99.14	98.71	98.71	99.14	**99.57**	99.57	99.29
	Bag	**78.45**	**80.60**	**79.74**	**76.72**	81.03	80.17	81.47	**83.19**	**77.59**	**79.74**	**81.03**	**79.98**
	Coat	45.26	54.31	53.02	60.78	58.62	53.88	53.45	50.43	56.03	49.57	48.28	53.06
	Mixed	74.43	78.30	77.44	79.02	79.45	77.73	77.87	77.44	77.59	76.29	76.29	77.44
3	Normal	**99.57**	99.57	99.57	99.14	**99.14**	99.14	98.71	**99.14**	99.14	99.14	98.71	99.18
	Bag	75.00	67.24	60.34	59.91	57.76	60.78	64.66	58.19	61.21	65.52	68.97	63.60
	Coat	55.60	66.81	63.79	65.09	65.09	62.07	60.34	55.17	56.03	56.03	57.33	60.31
	Mixed	76.72	77.87	74.57	74.71	73.99	73.99	74.57	70.83	72.13	73.56	75.00	74.36
4	Normal	**99.57**	99.57	**99.57**	**99.57**	98.71	99.14	98.71	**99.14**	98.71	99.14	98.71	99.14
	Bag	73.71	67.67	59.91	62.93	57.33	60.78	63.79	59.48	60.78	66.81	66.81	63.64
	Coat	63.36	69.83	66.38	68.97	65.95	63.79	59.91	59.91	59.91	61.21	61.21	63.68
	Mixed	78.88	79.02	75.29	77.16	73.99	74.57	74.14	72.84	73.13	75.72	75.57	75.48
5	Normal	**99.57**	99.57	99.14	99.14	98.71	99.14	**99.14**	**99.14**	98.71	99.14	99.14	99.14
	Bag	78.02	73.28	71.98	74.14	77.16	74.57	75.00	74.14	70.26	75.43	74.14	74.37
	Coat	79.74	82.33	80.60	80.60	78.45	72.84	74.14	74.57	76.29	78.02	76.29	77.63
	Mixed	**85.78**	85.06	83.91	84.63	84.77	82.18	82.76	82.61	81.75	**84.20**	83.19	83.71
6	Normal	99.57	99.57	**99.57**	98.71	98.71	99.14	**99.14**	**99.14**	99.14	99.14	98.71	99.14
	Bag	78.02	73.28	70.26	73.71	75.00	73.71	73.71	72.41	69.40	73.28	73.71	73.32
	Coat	78.45	81.47	78.02	80.60	77.59	73.71	75.00	74.57	75.86	75.43	77.16	77.08
	Mixed	85.34	84.77	82.61	84.34	83.76	82.18	82.61	82.04	81.47	82.61	**83.19**	83.18
7	Normal	**99.57**	**100**	99.14	**99.57**	98.71	**100**	98.71	98.71	99.14	99.14	99.57	99.29
	Bag	72.41	67.67	68.53	64.66	64.22	66.38	69.40	63.36	66.38	71.98	68.10	67.55
	Coat	74.57	78.02	79.74	75.43	76.72	78.88	72.41	74.14	72.84	69.40	71.98	74.92
	Mixed	82.18	81.90	82.47	79.89	79.89	81.75	80.17	78.74	79.45	80.17	79.89	80.59
8	Normal	**99.57**	99.57	99.14	**99.57**	98.28	99.57	98.28	98.28	98.71	98.71	99.57	99.02
	Bag	71.12	68.97	66.81	61.64	64.66	64.22	67.67	62.07	65.52	71.12	65.95	66.34
	Coat	76.29	77.59	80.17	78.45	77.59	78.02	73.28	71.55	72.84	74.14	74.57	75.86
	Mixed	82.33	82.04	82.04	79.89	80.17	80.60	79.74	77.30	79.02	81.32	80.03	80.41
9	Normal	**99.57**	99.14	98.71	99.14	97.84	99.14	98.71	98.28	97.41	98.71	98.28	98.63
	Bag	69.83	75.00	73.71	73.71	79.31	83.19	81.90	76.72	71.98	73.28	67.24	75.08
	Coat	**84.91**	**86.64**	**88.36**	83.19	**83.62**	**83.19**	**82.76**	**80.60**	**82.76**	**80.17**	**81.90**	**83.46**
	Mixed	84.77	**86.93**	**86.93**	**85.34**	**86.93**	**88.51**	**87.79**	**85.20**	**84.05**	84.05	82.47	**85.72**
10	Normal	**99.57**	99.14	98.28	99.14	97.84	99.57	98.28	98.28	97.41	98.71	98.28	98.59
	Bag	68.97	73.28	71.55	71.55	75.00	82.76	81.03	76.72	71.12	73.28	67.67	73.90
	Coat	83.19	85.34	87.93	**83.62**	**83.62**	**83.19**	82.33	80.17	81.90	79.31	81.03	82.88
	Mixed	83.91	85.92	85.92	84.77	85.49	88.51	87.21	85.06	83.48	83.76	82.33	85.12
11	Normal	**99.57**	**100**	**99.57**	**99.57**	98.71	99.57	98.71	98.71	99.14	**99.57**	99.14	99.29
	Bag	75.86	74.14	68.10	65.52	71.12	68.97	72.84	70.69	66.81	73.71	74.57	71.12
	Coat	50.00	62.07	60.78	62.50	62.50	62.50	61.21	54.74	61.64	56.03	56.90	59.17
	Mixed	75.14	78.74	76.15	75.86	77.44	77.01	77.59	74.71	75.86	76.44	76.87	76.53
12	Normal	**99.57**	**100**	98.71	**99.57**	98.28	99.57	98.28	98.28	98.28	99.14	99.14	98.98
	Bag	76.29	73.28	63.79	65.52	69.40	69.83	70.69	67.67	66.38	72.84	71.12	69.71
	Coat	57.76	65.95	62.50	65.09	65.95	62.50	61.64	57.76	64.22	60.34	62.07	62.34
	Mixed	77.87	79.74	75.00	76.72	77.87	77.30	76.87	74.57	76.29	77.44	77.44	77.01
13	Normal	**99.57**	99.14	99.14	**99.57**	97.84	99.14	98.28	98.28	97.41	99.14	98.71	98.75
	Bag	74.14	78.88	72.41	75.86	81.90	**85.34**	**83.19**	79.31	72.84	76.72	71.98	77.51
	Coat	77.16	72.41	72.41	74.14	71.55	66.81	69.83	68.10	72.41	66.38	73.28	71.32
	Mixed	83.62	83.48	81.32	83.19	83.76	83.76	83.76	81.90	80.89	80.75	81.32	82.52
14	Normal	**99.57**	99.14	99.14	99.14	97.84	99.14	98.28	97.84	97.41	99.14	98.71	98.67
	Bag	72.84	78.02	71.98	75.43	78.88	84.91	81.90	78.88	73.28	75.86	71.12	76.65
	Coat	73.28	71.55	69.40	72.41	72.84	66.81	66.38	66.38	72.41	63.36	72.41	69.75
	Mixed	81.90	82.90	80.17	82.33	83.19	83.62	82.18	81.03	81.03	79.45	80.75	81.69

Table 5-9: CGI Part scores fusion

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	99.43	99.71	99.43	98.71	97.84	97.56	97.84	96.84	97.56	98.99	**99.57**	98.50
	Bag	73.71	78.02	76.87	73.56	79.45	81.61	81.61	78.59	74.14	75.72	74.86	77.10
	Coat	78.02	80.89	80.32	81.61	82.90	84.91	82.76	78.74	79.74	76.29	75.57	80.16
	Mixed	83.72	86.21	85.54	84.63	86.73	88.03	87.40	84.72	83.81	83.67	83.33	85.25
2	Normal	**99.71**	**100**	**99.86**	**99.28**	97.56	97.84	**98.28**	**98.28**	98.28	99.14	**99.57**	98.89
	Bag	76.44	**79.74**	**79.31**	76.01	81.32	83.48	84.20	**81.32**	**77.73**	**77.30**	**77.73**	**79.51**
	Coat	44.11	54.45	58.19	66.09	67.24	66.67	64.80	60.92	60.34	46.70	43.97	57.59
	Mixed	73.42	78.07	79.12	80.46	82.04	82.66	82.42	80.17	78.78	74.38	73.75	78.66
3	Normal	**99.71**	99.86	99.57	98.85	**98.28**	97.84	98.13	**98.28**	**98.85**	99.14	99.28	98.89
	Bag	75.43	71.55	65.95	67.39	72.13	73.56	77.30	70.69	67.67	68.68	74.43	71.34
	Coat	60.06	70.26	71.98	75.57	77.73	75.72	72.13	66.95	65.95	63.65	64.37	69.49
	Mixed	78.40	80.56	79.17	80.60	82.71	82.38	82.52	78.64	77.49	77.16	79.36	79.91
4	Normal	**99.71**	99.71	99.28	98.71	97.99	97.70	98.13	98.13	98.56	99.14	99.28	98.76
	Bag	75.43	71.41	66.67	67.96	72.84	74.28	77.16	71.84	66.81	67.67	72.41	71.32
	Coat	68.82	73.28	74.71	78.88	79.17	76.44	73.71	71.41	68.68	70.69	68.39	73.11
	Mixed	81.32	81.47	80.22	81.85	83.33	82.81	83.00	80.46	78.02	79.17	80.03	81.06
5	Normal	99.57	99.57	99.14	98.85	97.84	97.27	97.84	97.84	97.56	98.71	99.14	98.48
	Bag	**77.73**	74.71	72.13	75.72	**81.75**	83.48	82.33	80.46	74.71	75.14	77.16	77.76
	Coat	82.04	84.63	84.05	86.78	85.20	83.62	83.91	82.18	82.61	80.75	81.90	83.42
	Mixed	**86.45**	86.30	85.11	**87.12**	**88.27**	88.12	**88.03**	**86.83**	84.96	**84.87**	**86.06**	**86.56**
6	Normal	99.57	99.43	98.99	98.85	97.84	97.41	97.41	97.99	97.70	98.71	99.14	98.46
	Bag	75.86	73.99	69.54	73.13	78.88	81.03	80.17	79.60	73.28	72.70	76.29	75.86
	Coat	80.75	84.20	82.76	85.63	82.76	83.19	83.62	81.32	80.32	78.30	81.32	82.20
	Mixed	85.39	85.87	83.76	85.87	86.49	87.21	87.07	86.30	83.76	83.24	85.58	85.51
7	Normal	99.57	99.57	98.71	98.13	97.84	97.56	97.41	96.41	97.70	98.99	99.43	98.30
	Bag	71.12	73.71	71.98	69.11	72.70	76.72	78.30	74.14	68.53	69.25	71.26	72.44
	Coat	77.87	83.19	83.91	83.33	84.48	85.49	82.90	82.04	81.75	78.45	76.44	81.81
	Mixed	82.85	85.49	84.87	83.52	85.01	86.59	86.21	84.20	82.66	82.23	82.38	84.18
8	Normal	99.57	99.43	98.71	98.13	96.98	97.41	96.98	95.98	97.84	98.85	99.43	98.12
	Bag	71.26	72.84	72.13	67.39	73.13	77.59	78.88	73.42	69.25	68.39	70.55	72.26
	Coat	81.03	84.91	84.34	84.05	86.35	85.49	84.34	82.33	81.32	80.32	79.45	83.09
	Mixed	83.96	85.73	85.06	83.19	85.49	86.83	86.73	83.91	82.81	82.52	83.14	84.49
9	Normal	99.43	99.14	97.70	97.41	96.98	96.84	96.41	95.55	97.13	98.13	98.56	97.57
	Bag	69.83	73.85	72.27	73.71	78.02	83.76	81.90	76.44	71.55	69.54	72.41	74.84
	Coat	**84.63**	**88.79**	**88.36**	**88.36**	**86.78**	**86.78**	**85.06**	**84.91**	**86.35**	**81.75**	**86.06**	**86.17**
	Mixed	84.63	**87.26**	**86.11**	86.49	87.26	**89.13**	87.79	85.63	**85.01**	83.14	85.68	86.19
10	Normal	99.43	98.85	97.70	97.41	96.41	96.84	96.26	95.40	97.13	98.28	98.42	97.47
	Bag	68.25	73.13	69.97	71.55	75.72	81.90	80.03	75.29	71.26	67.96	71.41	73.32
	Coat	83.62	87.79	87.79	87.21	86.06	85.92	84.34	84.63	85.49	80.17	85.34	85.31
	Mixed	83.76	86.59	85.15	85.39	86.06	88.22	86.88	85.11	84.63	82.14	85.06	85.36
11	Normal	**99.71**	**100**	99.57	**99.28**	97.84	**97.99**	**98.28**	**98.28**	98.42	**99.43**	99.43	**98.93**
	Bag	76.01	77.30	72.99	71.55	76.44	80.03	82.04	77.73	71.84	71.84	76.58	75.85
	Coat	54.45	64.51	67.67	72.27	73.85	74.43	69.54	66.09	67.24	57.90	57.90	65.99
	Mixed	76.72	80.60	80.08	81.03	82.71	84.15	83.29	80.70	79.17	76.39	77.97	80.26
12	Normal	**99.71**	99.86	99.43	99.14	97.27	97.41	98.13	98.13	98.28	99.28	99.28	98.72
	Bag	75.57	75.86	72.13	72.84	75.43	80.32	81.61	76.87	70.69	71.55	74.28	75.20
	Coat	61.78	67.82	69.97	74.28	76.15	76.44	71.84	69.40	69.54	62.07	63.36	69.33
	Mixed	79.02	81.18	80.51	82.09	82.95	84.72	83.86	81.47	79.50	77.63	78.98	81.08
13	Normal	**99.71**	99.43	98.99	98.28	96.84	97.56	97.70	97.70	97.41	98.85	98.71	98.29
	Bag	75.14	77.01	72.84	**78.02**	81.18	**86.64**	**85.78**	81.03	75.86	75.29	74.71	78.50
	Coat	76.58	75.86	77.44	81.47	79.74	79.31	78.02	78.02	77.73	69.68	76.72	77.32
	Mixed	83.81	84.10	83.09	85.92	85.92	87.84	87.16	85.58	83.67	81.27	83.38	84.70
14	Normal	**99.71**	99.28	99.14	98.71	96.84	97.56	97.84	97.56	97.27	98.99	98.85	98.34
	Bag	73.99	75.86	71.41	75.72	78.02	84.48	83.19	80.75	74.86	73.56	74.57	76.95
	Coat	75.29	73.71	76.44	80.75	79.45	79.74	77.30	77.59	77.16	68.10	76.87	76.58
	Mixed	83.00	82.95	82.33	85.06	84.77	87.26	86.11	85.30	83.09	80.22	83.43	83.96

Table 5-10: GHGI Part score fusion

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	**96.98**	98.71	99.14	98.28	98.71	98.71	98.71	97.41	96.55	96.98	96.12	97.84
	Bag	84.48	89.22	**93.10**	93.97	95.69	94.40	**96.12**	**93.10**	88.79	**91.38**	85.34	91.42
	Coat	90.52	89.22	90.09	87.07	87.93	86.64	83.19	84.05	85.78	84.48	84.91	86.72
	Mixed	**90.66**	92.39	94.11	93.10	94.11	93.25	92.67	91.52	90.37	90.95	88.79	91.99
2	Normal	96.12	**99.57**	**99.57**	98.28	98.28	**99.14**	**99.57**	**98.28**	97.41	98.71	96.98	98.35
	Bag	**85.34**	**90.52**	**93.10**	94.40	96.12	95.69	95.69	**93.10**	**92.67**	90.95	**87.07**	**92.24**
	Coat	88.36	89.22	89.66	88.79	89.66	85.78	84.05	84.05	86.21	84.05	81.03	86.44
	Mixed	89.94	93.10	94.11	93.82	94.68	93.53	93.10	91.81	92.10	91.24	88.36	92.35
3	Normal	95.69	**99.57**	98.71	99.14	**99.14**	**99.14**	98.71	**98.28**	**98.28**	98.71	**97.84**	**98.47**
	Bag	84.05	87.93	90.09	92.67	94.83	94.83	93.97	92.67	86.21	84.05	84.91	89.66
	Coat	89.66	91.38	92.67	**93.10**	89.66	87.93	86.21	85.78	86.64	88.79	86.21	88.91
	Mixed	89.80	92.96	93.82	**94.97**	94.54	93.97	92.96	92.24	90.37	90.52	**89.66**	92.35
4	Normal	96.12	98.71	98.71	**99.57**	**99.14**	**99.14**	98.71	97.84	**98.28**	**99.14**	97.41	98.43
	Bag	84.91	87.93	90.52	91.38	95.69	94.83	93.97	**93.10**	87.93	87.93	86.21	90.40
	Coat	89.22	91.81	93.97	91.38	88.79	**88.79**	86.21	86.21	86.21	87.50	85.34	88.68
	Mixed	90.09	92.82	94.40	94.11	94.54	94.25	92.96	92.39	90.80	91.52	89.66	92.50
5	Normal	93.97	97.41	98.28	98.71	98.71	98.28	97.41	96.55	96.55	97.84	96.12	97.26
	Bag	81.90	84.48	89.66	93.10	95.26	95.69	94.40	91.38	88.79	83.19	84.48	89.30
	Coat	89.66	90.95	92.67	91.81	90.09	87.93	87.93	86.64	88.36	88.79	**87.07**	**89.26**
	Mixed	88.51	90.95	93.53	94.54	94.68	93.97	93.25	91.52	91.24	89.94	89.22	91.94
6	Normal	93.97	97.41	97.84	98.28	98.71	97.84	97.41	96.98	96.98	97.84	95.69	97.18
	Bag	80.60	84.91	87.93	92.24	94.83	94.83	92.67	92.24	87.07	83.19	84.05	88.60
	Coat	89.66	89.66	91.38	92.24	87.50	86.64	87.07	84.05	86.21	87.93	86.64	88.09
	Mixed	88.07	90.66	92.39	94.25	93.68	93.10	92.39	91.09	90.09	89.66	88.79	91.29
7	Normal	96.12	98.71	98.28	98.28	**99.14**	**99.14**	98.71	96.98	95.69	96.55	94.40	97.45
	Bag	78.45	86.21	88.79	93.53	95.26	93.97	93.97	90.52	86.64	89.22	81.03	88.87
	Coat	91.38	91.38	93.10	90.52	90.95	87.93	87.07	86.21	86.64	89.22	85.78	89.11
	Mixed	88.65	92.10	93.39	94.11	95.11	93.68	93.25	91.24	89.66	91.67	87.07	91.81
8	Normal	96.12	98.71	98.71	98.28	98.71	**99.14**	98.71	97.41	96.12	96.55	95.26	97.61
	Bag	78.02	85.34	88.79	93.10	95.26	95.26	94.83	91.38	87.50	89.66	82.76	89.26
	Coat	**91.81**	**93.10**	93.10	90.09	90.09	**88.79**	87.07	85.78	87.07	87.93	84.48	89.03
	Mixed	88.65	92.39	93.53	93.82	94.68	94.40	93.53	91.52	90.23	91.38	87.50	91.97
9	Normal	95.69	97.84	97.84	98.28	98.28	98.28	97.41	96.12	95.69	94.83	92.67	96.63
	Bag	75.86	84.91	87.07	93.97	96.12	94.40	94.83	89.22	87.07	86.64	81.47	88.32
	Coat	90.52	91.81	92.24	89.66	90.09	88.36	87.50	**87.07**	87.07	89.22	86.64	89.11
	Mixed	87.36	91.52	92.39	93.97	94.83	93.68	93.25	90.80	89.94	90.23	86.93	91.35
10	Normal	95.69	96.98	97.84	97.41	96.98	97.84	96.55	96.98	96.12	94.83	93.10	96.39
	Bag	75.86	84.48	86.21	93.97	93.97	94.83	95.26	89.66	87.07	85.78	82.33	88.13
	Coat	90.09	90.95	91.81	89.22	88.79	87.07	87.50	85.78	86.21	88.79	86.21	88.40
	Mixed	87.21	90.80	91.95	93.53	93.25	93.25	93.10	90.80	89.80	89.80	87.21	90.97
11	Normal	96.12	98.28	98.71	98.28	98.71	98.71	99.14	97.84	96.98	98.28	97.41	98.04
	Bag	81.03	88.79	90.52	93.53	96.55	95.26	94.83	91.81	91.38	88.79	83.19	90.52
	Coat	90.52	91.81	92.67	92.67	90.52	87.93	**88.36**	86.64	86.64	87.07	86.21	89.18
	Mixed	89.22	92.96	93.97	94.83	95.26	93.97	**94.11**	92.10	91.67	91.38	88.94	92.58
12	Normal	96.55	98.71	98.28	99.14	98.71	98.71	97.84	97.84	96.98	98.71	96.98	98.04
	Bag	81.03	88.36	91.81	93.53	**96.98**	**96.12**	**96.12**	**93.10**	92.24	90.09	84.48	91.26
	Coat	89.66	92.24	**93.97**	90.09	90.95	88.36	87.07	**87.07**	**88.79**	87.93	85.34	89.22
	Mixed	89.08	**93.10**	**94.68**	94.25	**95.55**	**94.40**	93.68	**92.67**	**92.67**	**92.24**	88.94	**92.84**
13	Normal	93.97	97.84	97.84	97.84	97.41	97.84	97.41	96.98	96.98	97.41	94.83	96.94
	Bag	79.31	83.62	89.66	**94.83**	95.69	94.83	95.69	90.95	90.09	86.21	83.62	89.50
	Coat	89.66	90.95	92.24	90.52	**91.38**	**88.79**	87.93	**87.07**	87.93	**89.66**	85.34	89.22
	Mixed	87.64	90.80	93.25	94.40	94.83	93.82	93.68	91.67	91.67	91.09	87.93	91.89
14	Normal	93.97	97.84	97.41	98.28	96.98	97.84	96.98	96.98	96.55	97.41	95.26	96.87
	Bag	78.02	84.91	88.79	93.97	95.26	95.26	95.69	90.95	89.66	86.64	81.90	89.18
	Coat	90.09	90.52	92.24	89.22	89.22	87.50	87.07	84.91	87.50	89.22	85.34	88.44
	Mixed	87.36	91.09	92.82	93.82	93.82	93.53	93.25	90.95	91.24	91.09	87.50	91.50

Table 5-11: CGHGI Part score fusion

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	**96.98**	98.71	99.14	98.28	98.28	98.99	98.85	97.70	96.55	96.98	96.26	97.88
	Bag	84.05	88.79	92.53	93.82	95.40	94.68	**95.83**	92.39	89.08	**91.38**	84.77	91.16
	Coat	90.80	89.08	90.52	88.36	88.07	87.50	84.34	84.48	85.78	85.06	84.34	87.12
	Mixed	**90.61**	92.19	94.06	93.49	93.92	93.73	93.01	91.52	90.47	91.14	88.46	92.05
2	Normal	96.26	**99.28**	**99.57**	98.42	98.42	98.85	**99.28**	98.13	97.27	98.85	97.13	98.32
	Bag	**85.49**	**90.52**	**93.53**	94.25	96.55	95.40	95.55	**93.10**	**92.67**	91.09	**86.93**	**92.28**
	Coat	87.36	89.66	89.37	89.22	90.23	86.64	84.63	83.76	86.06	84.34	81.03	86.57
	Mixed	89.70	**93.15**	94.16	93.97	95.07	93.63	93.15	91.67	92.00	91.43	88.36	92.39
3	Normal	95.98	98.71	98.71	99.43	**99.14**	98.99	98.71	**98.42**	**98.28**	98.71	**97.84**	**98.45**
	Bag	84.20	87.21	90.52	92.96	95.55	94.83	93.82	92.53	87.21	84.34	85.20	89.85
	Coat	90.23	91.67	92.67	**93.25**	89.80	87.07	86.35	85.78	87.07	88.36	86.49	88.98
	Mixed	90.13	92.53	93.97	95.21	94.83	93.63	92.96	92.24	90.85	90.47	89.85	92.42
4	Normal	95.83	98.56	98.71	**99.86**	98.99	98.99	98.28	98.13	**98.28**	**98.99**	97.27	98.35
	Bag	84.48	88.22	90.09	91.09	95.55	94.68	93.97	92.39	88.07	87.93	86.21	90.24
	Coat	89.80	92.24	93.25	91.09	88.51	87.79	85.92	85.49	86.21	87.64	86.21	88.56
	Mixed	90.04	93.01	94.01	94.01	94.35	93.82	92.72	92.00	90.85	91.52	**89.89**	92.39
5	Normal	93.97	97.41	98.13	98.56	98.71	98.13	97.41	96.70	96.84	97.99	95.98	97.26
	Bag	81.75	83.76	89.22	93.10	95.26	95.40	94.25	91.67	88.65	82.47	83.48	89.00
	Coat	89.22	90.23	92.67	91.81	89.22	87.21	87.50	85.92	**88.07**	88.65	86.64	88.83
	Mixed	88.31	90.47	93.34	94.49	94.40	93.58	93.06	91.43	91.19	89.70	88.70	91.70
6	Normal	93.97	97.41	97.99	98.28	98.71	97.84	97.41	97.13	96.98	97.99	95.83	97.23
	Bag	81.18	84.05	87.93	92.10	94.97	94.40	92.39	91.67	87.64	82.04	83.62	88.36
	Coat	89.37	89.94	90.66	90.37	87.64	86.06	86.49	84.77	86.78	87.93	85.78	87.80
	Mixed	88.17	90.47	92.19	93.58	93.77	92.77	92.10	91.19	90.47	89.32	88.41	91.13
7	Normal	96.12	98.56	98.28	98.28	98.99	**99.14**	98.56	96.84	95.83	96.55	94.25	97.40
	Bag	77.44	86.35	88.79	92.82	95.40	94.25	93.97	90.95	86.78	88.94	81.32	88.82
	Coat	**91.38**	91.95	92.82	90.37	90.37	88.07	86.93	86.35	86.78	**88.94**	85.78	89.07
	Mixed	88.31	92.29	93.30	93.82	94.92	93.82	93.15	91.38	89.80	91.48	87.12	91.76
8	Normal	95.98	98.71	98.71	98.28	98.13	98.99	98.71	97.27	95.98	96.55	95.55	97.53
	Bag	77.59	85.92	89.51	92.39	95.26	95.11	94.68	91.52	87.07	89.22	82.61	89.17
	Coat	**91.38**	**92.96**	**93.68**	90.37	90.66	**89.66**	86.93	85.78	87.36	88.36	85.34	89.32
	Mixed	88.31	92.53	93.97	93.68	94.68	**94.59**	93.44	91.52	90.13	91.38	87.84	92.01
9	Normal	95.40	97.56	97.84	98.13	97.56	98.13	97.13	95.98	95.55	94.83	92.53	96.42
	Bag	76.01	84.63	86.93	94.40	95.83	94.83	94.97	89.94	86.78	85.63	80.89	88.26
	Coat	90.09	92.24	92.67	89.80	89.80	87.36	**87.79**	86.93	87.07	88.65	**86.78**	89.02
	Mixed	87.16	91.48	92.48	94.11	94.40	93.44	93.30	90.95	89.80	89.70	86.73	91.23
10	Normal	95.69	96.98	97.84	97.56	96.26	97.84	96.70	96.41	95.83	94.83	92.67	96.24
	Bag	75.86	84.63	86.78	93.25	94.68	95.26	94.83	90.23	86.35	85.63	80.60	88.01
	Coat	89.94	91.52	92.39	89.80	89.08	86.93	87.64	85.63	85.92	87.93	86.06	88.44
	Mixed	87.16	91.04	92.34	93.53	93.34	93.34	93.06	90.76	89.37	89.46	86.45	90.90
11	Normal	96.26	98.56	98.42	98.99	98.56	98.99	98.85	97.56	96.98	98.42	97.41	98.09
	Bag	81.32	87.93	89.94	94.11	96.41	95.40	94.83	92.39	92.10	89.22	82.76	90.58
	Coat	89.37	90.95	92.39	92.82	90.80	87.36	**87.79**	86.49	87.07	88.22	85.49	88.98
	Mixed	88.98	92.48	93.58	**95.31**	95.26	93.92	**93.82**	92.15	92.05	91.95	88.55	92.55
12	Normal	95.69	98.56	98.28	99.28	98.42	98.56	97.99	97.27	97.13	98.71	97.41	97.94
	Bag	80.75	88.36	91.24	93.82	**96.84**	**95.83**	95.69	92.96	91.95	90.23	84.34	91.09
	Coat	90.09	92.10	93.25	90.37	91.52	88.79	86.78	**87.36**	87.79	88.51	86.49	**89.37**
	Mixed	88.84	93.01	**94.25**	94.49	**95.59**	94.40	93.49	**92.53**	**92.29**	**92.48**	89.42	**92.80**
13	Normal	93.68	97.70	97.84	98.42	97.99	97.84	97.27	96.55	96.84	96.84	94.97	96.90
	Bag	79.45	84.34	90.09	**95.11**	96.41	95.11	95.40	91.09	89.94	86.35	83.76	89.73
	Coat	88.94	90.66	92.53	90.95	**91.81**	88.51	**87.79**	86.93	87.79	88.51	85.20	89.05
	Mixed	87.36	90.90	93.49	94.83	95.40	93.82	93.49	91.52	91.52	90.57	87.98	91.90
14	Normal	93.97	97.84	97.56	98.28	96.98	97.84	96.98	96.70	96.41	96.70	94.83	96.73
	Bag	79.45	84.91	88.07	94.25	95.40	95.26	95.40	91.24	89.22	86.21	82.04	89.22
	Coat	89.08	90.66	92.10	89.80	89.51	87.36	86.78	85.06	87.07	88.65	84.20	88.21
	Mixed	87.50	91.14	92.58	94.11	93.97	93.49	93.06	91.00	90.90	90.52	87.02	91.39

CGHGI had the best classification rate of 92.80% at fusion 12 with part 4 (head to chest) fused with part 10 (lower hip) as shown in Table 5.11. This rate slightly increased when compared with CGHGI part 1 in Table 5.6. The best view angle was 72° with the rate of 95.59% at fusion 12 when it was tested by a mixed appearance dataset. The best classification rate in the case of normal walking, walking with a bag and a coat testing was 98.47% at fusion 3, 92.24% at fusion 2 and 89.26% at fusion 5, respectively. Single part 1 in Table 5.6 always had better classification rate than fusion 1 to 6 in Table 5.6. Fusion 7 to 12 in Table 5.11 had a higher classification rate than the individual selected part.

5.2.3 Discussion

Summarized classification rates which were divided by gait representation and part fusion are shown in Table 5.12. The best average classification rates in case of normal walking, walking with a bag, walking with a coat and mixed appearances were 99.37%-GEI at fusion 1, 92.28%-CGHGI at fusion 2, 89.37%-CGHGI at fusion 12 and 92.84%-GHGI at fusion 12, respectively. Part 1 or full body had the highest classification rate of 92.65%-GHGI and 92.71%-CGHGI from section 5.1. When this part was fused with another part in GHGI and CGHGI at fusion 1-6, the fusions gave lower classification rate than individual part 1. Part 11 or the lower knee was one of the selected parts in fusion 5 and 9 that were the best fusion for GEI and CGI, respectively

Based on the discussion, the best four fusions for gait representations were selected by the classification rate of mixed appearances testing. There are:

- GEI: 85.72% at fusion 9, 85.12% at fusion 10, 83.71% at fusion 5 and 83.59% at fusion 1
- CGI: 86.56% at fusion 5, 86.19% a fusion 9, 85.51% at fusion 6 and 85.36% at fusion 10
- GHGI: 92.84% at fusion 12, 92.58% at fusion 11, 92.50% at fusion 4 and 92.35%at fusions 2 and 3
- CGHGI: 92.80% at fusion 12, 92.55% at fusion 11, 92.42% at fusion 3 and 92.39% at fusion 2 and 4

If a body part fusion which fuses full body with another part was considered, GEI usually increased classification rate except for fusion 3. Fusions 1, 5 and 6 increased the classification rate in CGI representation. For GHGI and CGHGI, all fusions 1-6 had lower classification rates than full body did.

If part 1 was excluded from this experiment, the best classification rate for each presentation was 85.72% for GEI at fusion 9, 86.19% for CGI at fusion 9, 92.84% for GHGI at fusion 12 and 92.80% for CGHGI at fusion 12. These fusions had higher classification rate than the best classification rate in the single part experiment. Fusion 7 to 14 usually had higher classification rate than individual selected parts except for GEI at fusions 7 and 8. Part 2 in GEI, at fusions 11 and 12 had a slightly increased classification rate when fused with another part. Part 2 in CGI was the best part in which its fusion results are over 84%. All GHGI and CGHGI fusions had their classification rate higher than 90%.

Table 5-12: Summarized correct classification rate of part score fusion experiment

Fusion	Appearance	GEI	CGEI	GHGI	CGHGI	Fusion	Appearance	GEI	CGEI	GHGI	CGHGI
1	Normal	**99.37**	98.50	97.84	97.88	8	Normal	99.02	98.12	97.61	97.53
	Bag	78.17	77.10	91.42	91.16		Bag	66.34	72.26	89.26	89.17
	Coat	73.24	80.16	86.72	87.12		Coat	75.86	83.09	89.03	89.32
	Mixed	83.59	85.25	91.99	92.05		Mixed	80.41	84.49	91.97	92.01
2	Normal	99.29	98.89	98.35	98.32	9	Normal	98.63	97.57	96.63	96.42
	Bag	**79.98**	**79.51**	**92.24**	**92.28**		Bag	75.08	74.84	88.32	88.26
	Coat	53.06	57.59	86.44	86.57		Coat	**83.46**	**86.17**	89.11	89.02
	Mixed	77.44	78.66	92.35	92.39		Mixed	**85.72**	86.19	91.35	91.23
3	Normal	99.18	98.89	**98.47**	**98.45**	10	Normal	98.59	97.47	96.39	96.24
	Bag	63.60	71.34	89.66	89.85		Bag	73.90	73.32	88.13	88.01
	Coat	60.31	69.49	88.91	88.98		Coat	82.88	85.31	88.40	88.44
	Mixed	74.36	79.91	92.35	92.42		Mixed	85.12	85.36	90.97	90.90
4	Normal	99.14	98.76	98.43	98.35	11	Normal	99.29	**98.93**	98.04	98.09
	Bag	63.64	71.32	90.40	90.24		Bag	71.12	75.85	90.52	90.58
	Coat	63.68	73.11	88.68	88.56		Coat	59.17	65.99	89.18	88.98
	Mixed	75.48	81.06	92.50	92.39		Mixed	76.53	80.26	92.58	92.55
5	Normal	99.14	98.48	97.26	97.26	12	Normal	98.98	98.72	98.04	97.94
	Bag	74.37	77.76	89.30	89.00		Bag	69.71	75.20	91.26	91.09
	Coat	77.63	83.42	**89.26**	88.83		Coat	62.34	69.33	89.22	**89.37**
	Mixed	83.71	**86.56**	91.94	91.70		Mixed	77.01	81.08	**92.84**	**92.80**
6	Normal	99.14	98.46	97.18	97.23	13	Normal	98.75	98.29	96.94	96.90
	Bag	73.32	75.86	88.60	88.36		Bag	77.51	78.50	89.50	89.73
	Coat	77.08	82.20	88.09	87.80		Coat	71.32	77.32	89.22	89.05
	Mixed	83.18	85.51	91.29	91.13		Mixed	82.52	84.70	91.89	91.90
7	Normal	99.29	98.30	97.45	97.40	14	Normal	98.67	98.34	96.87	96.73
	Bag	67.55	72.44	88.87	88.82		Bag	76.65	76.95	89.18	89.22
	Coat	74.92	81.81	89.11	89.07		Coat	69.75	76.58	88.44	88.21
	Mixed	80.59	84.18	91.81	91.76		Mixed	81.69	83.96	91.50	91.39

If any body parts (e.g. parts 5-8) negatively contribute to gait recognition in appearances with carrying or wearing objects, the remaining parts can be used to recognize a person especially in case of GHGI and CGHGI in which their fusions gave classification rate over 90%.

5.3 Part Image Fusion (PIF)

In the previous experiment in Section 5.2, two personal models are separately trained by using two body parts of a person then fusing scores for decision making. The experiment in this section fuses both selected parts into one image. An example of image fusion, which is the product of parts 1 and 11, is shown in Figure 5.4. In the same way as the single part experiment, this fused image is used as the input to the gait recognition system in Figure 5.1.

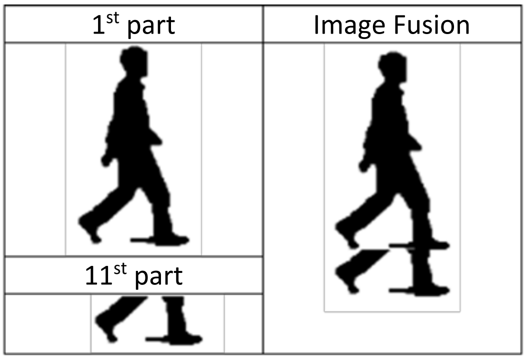


Figure 5-4: Image Fusion Example

5.3.1 Experimental Results

Image fusion concatenated two selected body parts into a single image. Four kind gait representations, GEI, CGI (D-3), GHGI and CGHGI (E-1), were exploited in this experiment. The detailed results of each representation are shown in Tables 5.13-5.16.

Image fusion GEI had the best average classification rate of 85.03% with fusion 9, which was generated from part 2 (head) and part 11 (lower knee), as demonstrated in Table 5.13. This classification rate slightly increased when compared with 82.16% GEI part 11 in Table 5.2. The best view angle was 90° from which fusion 9 has the classification rate of 87.36% when tested with the mixed appearance dataset. The best classification rate in case of normal walking, walking with a bag and a coat was 99.18% at fusions 1 and 11, 79.74% at fusion 13, and 83.66% at fusion 9, respectively. Six fusions, i.e. fusions 2, 4, 9, 10, 11 and 12 had a better classification rate than single selected parts. Additionally, only fusions 9 and 10 had a higher classification rate than single part 11 (lower knee).

Image fusion CGI with fusion 9 had the best classification rate of 86.81% when four normal walking datasets were used in training. The results are shown in Table 5.14. This rate slightly increased when compared with 84.15% CGI part 11 in Table 5.3. The best view angle was 90° and fusion 9 had the best classification rate. The best classification rate was 87.36% when tested by a mixed appearance dataset in this view angle. The best classification rate in case of normal walking, walking with a bag and a coat was 98.20% at fusion 2, 83.54% at fusion 2 and 87.46% at fusion 9, respectively. All fusions had higher classification rates than single selected parts. Additionally, except for fusion 14, all other fusions had higher classification rate than the best CGI single part (part 11).

Image fusion GHGI with fusion 9 had the best classification rate of 92.61% when four normal walking datasets were used in training, as shown in Table 5.15. This rate was slightly less than 92.65% GHGI part 1 in Table 5.4. The best view angle was 72° and the classification rate of fusion 1 was 95.11% when tested by a mixed appearance dataset. The best classification rate in case of normal walking, walking with a bag and a coat was 98.32% at fusions 1 and 2, 92.20% at fusion 1 and 88.64% at fusion 8, respectively. All fusions had classification rate greater than 90%, nonetheless, all fusions had a lower classification rate than single part 1 in Table 5.4.

Image fusion CGHGI with fusion 1, which was generated from parts 1 and 2 had the best classification rate of 92.72% when four normal walking datasets were used in training. The results are shown in Table 5.16. This classification rate was the same with 92.71% CGHGI part 1 in Table 5.5. The best view angle was 72° and fusion 9 classification rate was 94.97% when tested by mixed appearance datasets. The best classification rate in case of normal walking, walking with a bag and a coat was 98.51% at fusion 7, 92.48% at fusion 2 and 88.79% at fusion 8, respectively. Fusions 2-6 which were generated from part 1 and another part had a lower classification rate than single part 1. The other fusions had a higher classification rate than the single selected part. In addition, all fusions had higher classification rate than 90%.

Table 5-13: GEI Image fusion

Fusion	Appearance	View Angle											
		0	**18**	**36**	**54**	**72**	**90**	**108**	**126**	**144**	**162**	**180**	**Mean**
1	Normal	**99.57**	**100**	**99.57**	98.71	98.71	99.14	**99.14**	**99.57**	98.28	**99.14**	**99.14**	**99.18**
	Bag	**76.72**	73.71	73.28	67.67	69.83	67.24	70.69	71.55	70.69	73.28	78.45	72.10
	Coat	49.57	62.07	56.47	60.34	61.21	58.19	55.17	53.45	53.02	52.16	49.57	55.56
	Mixed	75.29	78.59	76.44	75.57	76.58	74.86	75.00	74.86	73.99	74.86	75.72	75.61
2	Normal	**99.57**	**100**	**99.57**	98.71	98.71	98.71	**99.14**	99.14	98.71	98.71	99.14	99.10
	Bag	**76.72**	74.57	**74.57**	68.53	74.57	69.83	72.84	73.28	72.41	73.71	**81.03**	73.82
	Coat	47.41	57.33	55.17	60.34	54.74	53.88	53.02	51.29	52.16	50.00	48.28	53.06
	Mixed	74.57	77.30	76.44	75.86	76.01	74.14	75.00	74.57	74.43	74.14	76.15	75.33
3	Normal	**99.57**	**100**	**99.57**	98.71	98.71	99.14	98.71	99.14	98.71	**99.14**	**99.14**	99.14
	Bag	74.57	68.53	68.53	60.78	60.78	61.64	66.38	63.36	64.66	69.40	72.84	66.50
	Coat	52.59	61.64	58.19	62.93	62.93	60.78	56.90	53.02	52.16	54.31	51.72	57.01
	Mixed	75.57	76.72	75.43	74.14	74.14	73.85	73.99	71.84	71.84	74.28	74.57	74.22
4	Normal	**99.57**	**100**	**99.57**	98.71	98.71	99.14	98.71	99.14	98.71	**99.14**	**99.14**	99.14
	Bag	75.43	68.10	69.40	63.36	59.91	64.22	67.67	64.22	62.50	69.40	71.98	66.93
	Coat	53.45	61.64	57.76	64.22	63.79	60.78	58.19	54.31	54.74	55.17	52.59	57.88
	Mixed	76.15	76.58	75.57	75.43	74.14	74.71	74.86	72.56	71.98	74.57	74.57	74.65
5	Normal	**99.57**	**100**	**99.57**	98.71	98.71	99.14	**99.14**	99.14	98.28	**99.14**	**99.14**	99.14
	Bag	75.86	72.84	72.84	67.67	71.12	68.10	72.84	70.26	68.10	72.41	78.45	71.87
	Coat	53.45	62.07	58.62	65.09	65.52	62.07	61.21	56.90	56.90	53.88	55.60	59.21
	Mixed	76.29	78.30	77.01	77.16	78.45	76.44	77.73	75.43	74.43	75.14	77.73	76.74
6	Normal	**99.57**	**100**	**99.57**	98.71	98.71	99.14	98.71	99.14	98.28	**99.14**	**99.14**	99.10
	Bag	75.00	71.55	70.69	67.67	68.97	67.67	72.84	68.97	67.67	72.84	76.72	70.96
	Coat	51.72	62.93	57.33	62.50	63.79	59.48	60.78	55.60	56.90	54.31	53.02	58.03
	Mixed	75.43	78.16	75.86	76.29	77.16	75.43	77.44	74.57	74.28	75.43	76.29	76.03
7	Normal	**99.57**	99.57	98.71	**99.57**	**99.14**	99.14	98.71	99.14	**99.14**	**99.14**	98.71	99.14
	Bag	67.24	63.36	60.78	54.74	53.88	55.60	61.21	57.76	53.45	59.48	61.64	59.01
	Coat	62.50	71.55	70.26	68.53	67.67	68.97	60.34	60.34	58.62	59.91	62.50	64.66
	Mixed	76.44	78.16	76.58	74.28	73.56	74.57	73.42	72.41	70.40	72.84	74.28	74.27
8	Normal	99.14	99.57	98.71	**99.57**	**99.14**	99.14	98.71	99.14	98.71	98.71	98.71	99.02
	Bag	65.52	62.93	61.21	56.90	54.74	57.33	63.36	56.90	53.45	60.34	57.76	59.13
	Coat	70.26	76.29	74.14	71.55	74.57	71.55	64.22	63.79	63.36	66.81	69.83	69.67
	Mixed	78.30	79.60	78.02	76.01	76.15	76.01	75.43	73.28	71.84	75.29	75.43	75.94
9	Normal	99.14	99.57	98.71	98.71	**99.14**	99.14	**99.14**	99.14	98.28	**99.14**	97.84	98.90
	Bag	69.40	68.10	72.41	70.26	75.86	81.90	78.45	75.43	69.83	71.12	65.09	72.53
	Coat	**86.64**	**87.50**	**87.93**	**87.07**	**84.48**	81.03	**81.90**	**80.60**	**79.74**	**79.31**	**84.05**	**83.66**
	Mixed	**85.06**	**85.06**	**86.35**	**85.34**	**86.49**	**87.36**	**86.49**	**85.06**	**82.61**	**83.19**	**82.33**	**85.03**
10	Normal	98.71	99.57	98.71	98.28	98.71	98.71	**99.14**	99.14	98.28	**99.14**	97.84	98.75
	Bag	67.67	67.24	69.83	68.97	72.84	78.88	78.02	74.14	66.81	69.83	64.22	70.77
	Coat	85.34	85.34	87.50	84.91	83.19	**81.47**	80.60	78.88	78.45	76.72	83.19	82.33
	Mixed	83.91	84.05	85.34	84.05	84.91	86.35	85.92	84.05	81.18	81.90	81.75	83.95
11	Normal	99.57	**100**	**99.57**	98.71	98.71	**99.57**	98.71	99.14	98.71	**99.14**	**99.14**	**99.18**
	Bag	72.84	68.10	68.97	62.07	64.22	67.24	70.69	67.24	63.36	69.83	71.98	67.87
	Coat	52.59	62.93	59.48	63.36	63.79	62.07	55.17	52.59	54.31	54.74	55.60	57.88
	Mixed	75.00	77.01	76.01	74.71	75.57	76.29	74.86	72.99	72.13	74.57	75.57	74.97
12	Normal	**99.57**	**100**	**99.57**	98.28	98.71	99.14	**99.14**	99.14	98.71	**99.14**	98.71	99.10
	Bag	72.41	68.53	67.67	65.52	67.24	70.69	72.41	67.67	61.21	70.26	70.69	68.57
	Coat	59.05	68.97	62.07	65.52	62.50	62.07	57.76	56.03	57.76	55.60	59.48	60.62
	Mixed	77.01	79.17	76.44	76.44	76.15	77.30	76.44	74.28	72.56	75.00	76.29	76.10
13	Normal	**99.57**	**100**	99.14	98.28	98.71	98.71	**99.14**	98.71	98.28	**99.14**	**99.14**	98.98
	Bag	76.29	**77.59**	72.41	**78.45**	**82.33**	**85.34**	84.05	**82.76**	**79.31**	**78.88**	79.74	**79.74**
	Coat	58.19	68.97	67.67	68.97	65.95	60.78	62.50	62.50	60.34	58.19	60.78	63.17
	Mixed	78.02	82.18	79.74	81.90	82.33	81.61	81.90	81.32	79.31	78.74	79.89	80.63
14	Normal	**99.57**	**100**	99.14	98.28	98.71	98.71	**99.14**	99.14	97.84	**99.14**	**99.14**	98.98
	Bag	74.14	74.57	71.98	76.29	**82.33**	84.05	**84.48**	81.47	76.29	77.16	76.29	78.10
	Coat	54.74	67.67	63.36	66.81	65.52	56.90	61.21	60.34	59.48	54.31	59.48	60.89
	Mixed	76.15	80.75	78.16	80.46	82.18	79.89	81.61	80.32	77.87	76.87	78.30	79.32

Table 5-14: CGI Image fusion

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	99.14	**100**	99.57	**98.28**	96.12	94.40	95.26	97.41	97.41	98.28	**100**	97.81
	Bag	78.45	85.34	82.33	**83.19**	**84.91**	**87.07**	**86.64**	83.62	83.62	81.47	80.60	83.39
	Coat	59.91	76.29	85.34	87.50	89.22	85.78	87.93	84.48	79.74	69.83	61.64	78.88
	Mixed	79.17	87.21	**89.08**	**89.66**	**90.09**	**89.08**	89.94	**88.51**	86.93	83.19	80.75	86.69
2	Normal	99.14	**100**	99.57	**98.28**	**96.98**	95.26	**96.55**	97.41	97.41	**99.57**	**100**	**98.20**
	Bag	77.59	**85.78**	**85.78**	82.33	**84.91**	86.64	85.78	**84.05**	83.62	**82.33**	80.17	**83.54**
	Coat	53.45	70.69	80.17	82.76	85.78	84.91	84.05	78.45	76.72	62.07	55.60	74.06
	Mixed	76.72	85.49	88.51	87.79	89.22	88.94	88.79	86.64	85.92	81.32	78.59	85.27
3	Normal	99.14	**100**	**100**	97.84	95.69	94.40	95.69	**97.84**	**98.71**	98.28	99.57	97.92
	Bag	78.02	85.34	79.31	79.74	83.19	85.34	85.78	**84.05**	83.62	78.88	81.03	82.21
	Coat	59.91	73.71	81.03	84.91	87.07	86.64	84.48	80.60	77.16	69.40	62.07	77.00
	Mixed	79.02	86.35	86.78	87.50	88.65	88.79	88.65	87.50	86.49	82.18	80.89	85.71
4	Normal	98.71	**100**	**100**	97.84	95.26	94.83	95.69	96.98	98.28	98.71	99.57	97.81
	Bag	77.59	84.91	79.31	78.02	82.33	83.19	83.62	83.62	**84.48**	78.88	81.03	81.54
	Coat	61.64	74.57	81.47	84.48	86.21	84.91	84.05	80.60	78.88	70.26	62.50	77.23
	Mixed	79.31	86.49	86.93	86.78	87.93	87.64	87.79	87.07	**87.21**	82.61	81.03	85.53
5	Normal	99.14	**100**	**100**	97.84	95.26	94.83	95.26	97.41	97.84	97.41	**100**	97.73
	Bag	**80.17**	85.78	81.90	81.47	**84.91**	86.64	85.34	81.90	81.90	81.03	**82.33**	83.03
	Coat	61.64	77.16	85.34	87.07	**89.22**	85.78	**88.79**	83.62	80.60	71.12	64.66	79.55
	Mixed	80.32	**87.64**	**89.08**	88.79	89.80	**89.08**	89.80	87.64	86.78	83.19	82.33	86.77
6	Normal	98.71	**100**	99.57	97.84	95.69	94.83	96.12	97.41	97.84	97.41	**100**	97.77
	Bag	**80.17**	85.34	81.90	80.60	84.48	86.64	86.21	81.90	82.76	81.47	81.90	83.03
	Coat	61.21	76.72	84.91	87.07	89.22	85.78	87.93	83.19	79.74	71.12	63.36	79.11
	Mixed	80.03	87.36	88.79	88.51	89.80	**89.08**	**90.09**	87.50	86.78	83.33	81.75	86.64
7	Normal	**99.57**	99.57	98.71	96.98	95.69	**95.69**	95.26	96.98	98.28	98.28	99.57	97.69
	Bag	77.59	76.29	74.57	72.84	76.72	78.88	81.47	77.59	76.72	71.55	74.57	76.25
	Coat	75.00	81.90	84.05	84.48	85.34	84.05	82.76	80.60	79.74	77.16	74.57	80.88
	Mixed	84.05	85.92	85.78	84.77	85.92	86.21	86.49	85.06	84.91	82.33	82.90	84.94
8	Normal	99.14	99.14	98.71	96.12	95.26	94.40	94.83	96.12	97.84	99.14	99.57	97.30
	Bag	76.29	75.86	71.55	72.41	75.86	78.02	82.76	77.16	75.86	71.12	75.00	75.63
	Coat	77.16	85.34	83.19	84.05	86.64	82.33	82.33	79.31	81.90	81.47	79.31	82.09
	Mixed	84.20	86.78	84.48	84.20	85.92	84.91	86.64	84.20	85.20	83.91	84.63	85.01
9	Normal	**99.57**	98.71	98.28	96.12	95.26	93.97	94.40	94.83	96.98	97.41	98.28	96.71
	Bag	75.86	73.71	75.86	74.14	78.45	82.33	80.60	77.16	72.41	72.84	75.43	76.25
	Coat	**85.34**	**90.09**	**90.09**	**89.22**	86.64	**87.07**	86.64	**84.91**	**86.64**	**87.93**	**87.50**	**87.46**
	Mixed	**86.93**	87.50	88.07	86.49	86.78	87.79	87.21	85.63	85.34	**86.06**	**87.07**	**86.81**
10	Normal	**99.57**	98.71	97.41	95.69	95.26	94.40	93.97	94.83	96.98	97.41	98.28	96.59
	Bag	71.98	73.71	72.41	72.84	75.43	80.17	80.60	77.16	69.40	71.12	74.57	74.49
	Coat	84.91	89.66	89.22	88.36	86.21	86.64	85.78	84.48	84.48	85.78	86.64	86.56
	Mixed	85.49	87.36	86.35	85.63	85.63	87.07	86.78	85.49	83.62	84.77	86.49	85.88
11	Normal	99.14	**100**	99.57	97.84	95.69	94.83	**96.55**	97.41	98.28	98.71	**100**	98.00
	Bag	78.88	85.34	78.88	79.74	81.47	83.62	84.91	83.19	81.90	79.74	79.31	81.54
	Coat	59.48	73.28	81.03	84.91	84.91	85.78	84.48	78.02	75.86	65.95	64.22	76.18
	Mixed	79.17	86.21	86.49	87.50	87.36	88.07	88.65	86.21	85.34	81.47	81.18	85.24
12	Normal	99.14	99.57	**100**	97.41	95.26	94.83	96.12	96.98	97.41	98.71	99.57	97.73
	Bag	78.02	84.05	78.45	76.29	78.88	82.76	82.33	82.33	82.33	81.47	79.31	80.56
	Coat	59.48	75.43	80.17	84.91	84.91	86.21	83.19	80.60	74.57	66.38	67.67	76.68
	Mixed	78.88	86.35	86.21	86.21	86.35	87.93	87.21	86.64	84.77	82.18	82.18	84.99
13	Normal	99.14	**100**	**100**	97.84	96.55	95.26	94.83	96.55	96.98	98.28	99.57	97.73
	Bag	77.59	81.90	83.62	77.59	82.33	86.64	85.34	81.90	80.17	81.47	81.47	81.82
	Coat	59.91	69.40	75.00	78.88	83.62	83.19	83.62	77.59	72.84	63.36	61.21	73.51
	Mixed	78.88	83.76	86.21	84.77	87.50	88.36	87.93	85.34	83.33	81.03	80.75	84.35
14	Normal	99.14	**100**	**100**	97.41	95.26	95.26	95.69	96.98	96.98	98.71	99.57	97.73
	Bag	76.72	81.90	81.47	77.16	80.60	84.05	85.34	81.03	79.74	**82.33**	81.47	81.07
	Coat	58.19	66.38	73.28	78.88	80.17	83.19	81.90	77.59	71.55	61.21	59.05	71.94
	Mixed	78.02	82.76	84.91	84.48	85.34	87.50	87.64	85.20	82.76	80.75	80.03	83.58

Table 5-15: GHGI Image fusion

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	95.69	98.71	**99.14**	99.14	98.71	**98.71**	**98.71**	**98.71**	97.84	98.28	**97.84**	**98.32**
	Bag	**87.07**	89.66	**92.67**	92.24	96.98	96.12	96.55	**93.97**	90.95	**91.38**	86.64	**92.20**
	Coat	89.66	91.38	90.52	89.22	**89.66**	86.64	84.48	82.76	**87.07**	86.21	82.76	87.30
	Mixed	**90.80**	93.25	**94.11**	**93.53**	**95.11**	93.82	93.25	91.81	**91.95**	**91.95**	89.08	**92.61**
2	Normal	95.69	98.71	**99.14**	99.14	98.71	**98.71**	**98.71**	97.84	97.41	97.41	97.41	98.08
	Bag	86.21	88.79	**92.67**	92.24	96.55	96.55	96.12	**93.97**	91.38	**91.38**	87.93	92.16
	Coat	88.79	89.66	88.36	87.07	89.66	85.34	84.05	80.60	83.62	83.62	81.03	85.62
	Mixed	90.23	92.39	93.39	92.82	94.97	93.53	92.96	90.80	90.80	90.80	88.79	91.95
3	Normal	95.69	98.71	**99.14**	99.14	98.71	**98.71**	**98.71**	98.28	97.84	98.71	**97.84**	**98.32**
	Bag	85.34	88.79	91.38	92.24	95.26	94.83	94.83	92.67	89.66	88.79	87.50	91.03
	Coat	87.93	92.67	89.66	89.22	86.64	87.07	83.62	80.17	83.62	85.34	82.33	86.21
	Mixed	89.66	93.39	93.39	**93.53**	93.53	93.53	92.39	90.37	90.37	90.95	89.22	91.85
4	Normal	95.69	98.71	98.71	99.14	98.71	**98.71**	**98.71**	98.28	97.84	97.84	**97.84**	98.20
	Bag	84.91	**89.66**	90.95	91.81	96.12	94.83	95.26	93.53	90.52	90.09	87.07	91.34
	Coat	89.66	92.24	89.66	88.36	86.64	87.50	83.62	81.03	83.62	85.34	82.76	86.40
	Mixed	90.09	93.53	93.10	93.10	93.82	93.68	92.53	90.95	90.66	91.09	89.22	91.98
5	Normal	95.69	98.71	98.71	99.14	98.71	**98.71**	**98.71**	98.28	**98.28**	98.28	97.41	98.24
	Bag	84.91	89.22	90.95	92.24	96.55	96.98	95.26	93.10	90.09	89.66	88.36	91.58
	Coat	89.22	93.10	91.38	87.93	87.50	87.50	84.05	83.19	85.34	86.21	84.91	87.30
	Mixed	89.94	**93.68**	93.68	93.10	94.25	**94.40**	92.67	91.52	91.24	91.38	**90.23**	92.37
6	Normal	95.69	98.71	98.71	99.14	98.28	**98.71**	**98.71**	98.28	**98.28**	98.28	97.41	98.20
	Bag	84.48	88.79	90.95	91.81	96.12	96.98	94.83	93.53	89.66	89.66	86.64	91.22
	Coat	88.79	**93.53**	90.09	88.36	87.50	87.07	83.62	83.19	85.34	86.21	83.19	86.99
	Mixed	89.66	**93.68**	93.25	93.10	93.97	94.25	92.39	91.67	91.09	91.38	89.08	92.14
7	Normal	**96.12**	**99.14**	98.71	**99.57**	98.71	**98.71**	97.84	97.84	97.84	**99.14**	97.41	98.28
	Bag	81.47	87.50	88.36	89.22	94.40	94.40	94.83	90.52	86.64	86.64	83.19	88.83
	Coat	86.64	92.67	92.24	89.22	86.64	87.93	84.48	84.91	**87.07**	87.93	84.91	87.70
	Mixed	88.07	93.10	93.10	92.67	93.25	93.68	92.39	91.09	90.52	91.24	88.51	91.60
8	Normal	95.69	97.84	98.71	99.14	**99.14**	**98.71**	97.41	97.41	97.84	98.28	96.55	97.88
	Bag	82.76	85.34	87.07	88.36	94.40	93.97	93.53	88.79	86.64	85.78	82.76	88.13
	Coat	88.79	93.53	**93.53**	89.66	88.79	**88.36**	85.34	**85.34**	86.64	**88.36**	**86.64**	**88.64**
	Mixed	89.08	92.24	93.10	92.39	94.11	93.68	92.10	90.52	90.37	90.80	88.65	91.55
9	Normal	95.26	98.28	98.28	**99.57**	98.71	97.84	97.41	98.28	96.55	95.69	95.69	97.41
	Bag	81.90	83.19	86.64	90.09	95.26	96.12	93.97	87.93	85.34	84.05	84.91	88.13
	Coat	**90.52**	91.38	90.52	89.22	89.22	87.07	**85.78**	83.62	**87.07**	85.78	86.21	87.85
	Mixed	89.22	90.95	91.81	92.96	94.40	93.68	92.39	89.94	89.66	88.51	88.94	91.13
10	Normal	94.83	98.28	98.28	**99.57**	97.84	97.84	96.98	97.41	96.55	96.12	96.12	97.26
	Bag	83.62	83.19	85.34	87.50	93.53	94.83	93.10	88.36	85.78	84.05	84.48	87.62
	Coat	90.09	91.38	88.79	87.50	88.36	85.34	**85.78**	84.48	85.78	84.48	85.78	87.07
	Mixed	89.51	90.95	90.80	91.52	93.25	92.67	91.95	90.09	89.37	88.22	88.79	90.65
11	Normal	**96.12**	98.71	98.71	99.14	98.71	**98.71**	98.28	**98.71**	97.84	97.84	**97.84**	98.24
	Bag	86.21	87.50	90.95	91.81	96.98	96.12	96.55	**93.97**	89.22	89.22	87.50	91.46
	Coat	88.36	91.81	91.38	**89.66**	87.50	87.07	85.78	84.05	85.34	87.07	84.05	87.46
	Mixed	90.23	92.67	93.68	**93.53**	94.40	93.97	**93.53**	**92.24**	90.80	91.38	89.80	92.39
12	Normal	**96.12**	98.71	98.71	99.14	98.71	**98.71**	97.84	97.84	96.98	97.84	96.98	97.96
	Bag	84.48	87.50	91.38	92.24	96.55	95.26	96.12	**93.97**	89.22	88.36	87.50	91.14
	Coat	89.22	92.67	90.95	89.22	87.07	87.50	85.78	83.62	85.78	**88.36**	84.91	87.74
	Mixed	89.94	92.96	93.68	**93.53**	94.11	93.82	93.25	91.81	90.66	91.52	89.80	92.28
13	Normal	**96.12**	98.71	98.71	98.71	97.84	97.41	97.41	96.55	96.98	96.98	96.55	97.45
	Bag	83.62	88.36	92.24	**93.10**	**97.41**	**97.41**	97.41	92.24	**91.38**	88.36	**88.79**	91.85
	Coat	87.93	90.09	90.09	86.21	88.36	86.21	84.05	82.33	82.33	83.62	83.19	85.85
	Mixed	89.22	92.39	93.68	92.67	94.54	93.68	92.96	90.37	90.23	89.66	89.51	91.72
14	Normal	**96.12**	98.71	**99.14**	98.28	97.84	97.41	97.41	96.55	96.98	96.98	96.55	97.45
	Bag	84.48	88.36	90.95	92.24	95.69	96.55	**97.84**	92.67	90.95	89.22	**88.79**	91.61
	Coat	86.64	89.22	87.50	84.91	86.64	85.34	82.33	81.90	82.76	84.05	81.90	84.84
	Mixed	89.08	92.10	92.53	91.81	93.39	93.10	92.53	90.37	90.23	90.09	89.08	91.30

Table 5-16: CGHGI Image fusion

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Mean
1	Normal	95.69	**99.57**	**99.14**	99.14	98.71	98.71	**98.71**	98.71	**98.28**	98.71	97.41	98.43
	Bag	**88.36**	89.22	**91.81**	91.81	96.55	96.55	96.55	**94.40**	90.95	**91.81**	86.64	92.24
	Coat	88.36	91.81	89.66	90.09	89.66	87.93	84.91	82.76	85.78	87.07	84.48	87.50
	Mixed	**90.80**	93.53	93.53	**93.68**	**94.97**	94.40	93.39	91.95	**91.67**	**92.53**	89.51	**92.72**
2	Normal	95.69	99.14	98.71	99.14	98.71	98.71	**98.71**	98.71	97.41	97.41	97.41	98.16
	Bag	87.07	**90.09**	**91.81**	**93.10**	96.98	**96.98**	96.12	**94.40**	**91.38**	91.38	87.93	**92.48**
	Coat	87.50	89.22	88.79	87.50	89.22	85.78	82.33	81.03	84.05	84.48	80.17	85.46
	Mixed	90.09	92.82	93.10	93.25	**94.97**	93.82	92.39	91.38	90.95	91.09	88.51	92.03
3	Normal	95.69	99.14	98.71	99.14	**99.14**	98.71	**98.71**	98.28	97.84	**99.14**	**97.84**	98.39
	Bag	85.78	89.22	90.52	90.95	95.26	95.26	95.69	93.53	90.09	89.22	86.21	91.07
	Coat	87.93	90.95	89.66	89.22	86.64	87.93	84.91	80.17	84.05	85.78	82.76	86.36
	Mixed	89.80	93.10	92.96	93.10	93.68	93.97	93.10	90.66	90.66	91.38	88.94	91.94
4	Normal	96.12	99.14	98.71	99.14	98.71	98.71	**98.71**	98.28	97.84	98.71	**97.84**	98.35
	Bag	84.91	88.79	90.09	90.52	95.69	94.83	94.83	93.53	90.09	88.79	85.78	90.71
	Coat	88.79	92.67	89.22	89.22	86.64	88.36	85.78	81.03	84.48	85.34	83.19	86.79
	Mixed	89.94	93.53	92.67	92.96	93.68	93.97	93.10	90.95	90.80	90.95	88.94	91.95
5	Normal	95.69	98.71	**99.14**	**99.57**	98.71	98.71	**98.71**	98.28	**98.28**	98.71	97.41	98.35
	Bag	86.21	89.22	90.09	90.09	96.12	96.55	95.26	93.97	90.52	89.22	87.07	91.30
	Coat	88.79	91.81	90.09	88.79	88.36	87.93	84.05	83.19	86.21	87.07	84.05	87.30
	Mixed	90.23	93.25	93.10	92.82	94.40	94.40	92.67	91.81	**91.67**	91.67	89.51	92.32
6	Normal	95.69	98.71	**99.14**	**99.57**	98.28	98.71	**98.71**	98.28	**98.28**	98.28	**97.84**	98.32
	Bag	85.78	89.66	90.52	90.52	95.69	**96.98**	95.26	93.97	90.09	89.66	86.64	91.34
	Coat	88.36	92.24	90.09	87.93	87.93	88.36	83.62	83.19	86.21	86.64	84.05	87.15
	Mixed	89.94	93.53	93.25	92.67	93.97	**94.68**	92.53	91.81	91.52	91.52	89.51	92.27
7	Normal	96.12	**99.57**	**99.14**	**99.57**	**99.14**	98.71	98.28	98.28	97.84	**99.14**	**97.84**	**98.51**
	Bag	84.05	87.50	87.07	89.22	93.97	95.69	95.26	90.09	86.64	87.07	82.33	88.99
	Coat	87.50	**93.97**	90.95	89.66	88.36	87.93	85.34	**85.34**	**88.36**	87.93	85.34	88.24
	Mixed	89.22	**93.68**	92.39	92.82	93.82	94.11	92.96	91.24	90.95	91.38	88.51	91.91
8	Normal	96.12	97.84	**99.14**	**99.57**	98.28	**99.14**	98.28	97.41	97.84	98.71	96.98	98.12
	Bag	81.90	86.21	86.21	87.93	94.40	94.40	93.53	89.66	86.21	84.91	81.90	87.93
	Coat	90.09	93.53	**93.10**	88.79	89.22	**89.22**	**86.21**	84.91	87.07	86.64	**87.93**	**88.79**
	Mixed	89.37	92.53	92.82	92.10	93.97	94.25	92.67	90.66	90.37	90.09	88.94	91.61
9	Normal	94.83	98.28	98.71	**99.57**	98.71	98.28	97.41	96.98	96.98	96.12	96.55	97.49
	Bag	81.90	82.33	87.93	87.93	95.26	95.26	93.10	90.95	86.21	84.48	85.78	88.28
	Coat	90.95	92.24	90.95	88.36	**90.95**	87.50	86.21	**85.34**	87.50	85.34	86.21	88.32
	Mixed	89.22	90.95	92.53	91.95	**94.97**	93.68	92.24	91.09	90.23	88.65	89.51	91.37
10	Normal	94.83	98.28	98.71	99.14	98.28	97.84	96.98	96.98	96.98	96.55	96.55	97.37
	Bag	81.47	83.19	85.34	84.91	93.53	94.40	93.10	89.22	86.21	84.05	85.34	87.34
	Coat	**91.38**	91.81	89.22	88.36	89.22	86.64	85.78	84.48	86.21	85.78	86.21	87.74
	Mixed	89.22	91.09	91.09	90.80	93.68	92.96	91.95	90.23	89.80	88.79	89.37	90.82
11	Normal	96.12	**99.57**	**99.14**	99.14	**99.14**	98.71	98.28	**99.14**	97.84	98.28	**97.84**	98.47
	Bag	85.78	88.79	90.95	91.38	96.98	96.12	95.69	93.97	89.22	88.36	87.93	91.38
	Coat	87.50	90.52	90.09	**90.09**	88.79	87.93	84.91	84.48	86.64	87.07	84.05	87.46
	Mixed	89.80	92.96	93.39	93.53	**94.97**	94.25	92.96	**92.53**	91.24	91.24	89.94	92.44
12	Normal	96.12	99.14	98.71	99.14	98.71	98.71	98.28	98.28	97.41	97.84	97.41	98.16
	Bag	85.78	88.36	90.95	92.24	96.55	95.69	95.69	93.97	88.36	88.79	86.64	91.18
	Coat	87.93	90.95	91.38	89.22	87.50	87.07	85.78	84.05	87.50	**89.22**	86.21	87.89
	Mixed	89.94	92.82	**93.68**	93.53	94.25	93.82	93.25	92.10	91.09	91.95	**90.09**	92.41
13	Normal	**96.55**	98.71	98.71	99.14	97.84	97.84	97.41	96.98	97.41	96.98	96.98	97.69
	Bag	84.05	88.36	90.52	92.24	**97.41**	**96.98**	**97.41**	92.24	90.95	90.52	**89.22**	91.81
	Coat	88.36	90.52	88.36	85.78	87.93	87.07	85.78	83.19	82.76	84.05	83.62	86.13
	Mixed	89.66	92.53	92.53	92.39	94.40	93.97	**93.53**	90.80	90.37	90.52	89.94	91.88
14	Normal	**96.55**	98.71	98.71	99.14	96.98	97.41	97.41	96.98	96.98	96.98	96.55	97.49
	Bag	84.48	88.36	90.09	91.81	96.12	96.12	96.98	92.67	90.95	89.66	87.93	91.38
	Coat	87.93	90.09	87.07	86.21	87.07	85.78	83.19	82.76	81.47	83.62	83.19	85.31
	Mixed	89.66	92.39	91.95	92.39	93.39	93.10	92.53	90.80	89.80	90.09	89.22	91.39

5.3.2 Discussion

Classification rates, which are against gait representations and part fusions, are presented in Table 5.17. The best average classification rate in case of normal walking, walking with a bag, walking with a coat and mixed appearances is 99.18% GEI at fusion 1 and 11, 92.48%-CGHGI at fusion 2, 88.79%-CGHGI at fusion 8 and 92.72%-GHGI at fusion 1, respectively. Part 1 (full body), which has an entire body silhouette, has the highest classification rate at 92.65% GHGI and 92.71% CGHGI from Section 5.1. When part 1 is fused with another part in GHGI and CGHGI at fusions 1-6, except CGHGI at fusion 1, all other fusions gives lower classification rate than part 1 only. Part 11 (lower knee) which has classification rate of 82.16%-GEI and 84.15%-CGI, is one selected part of the best at fusion 9 of GEI and CGI and the second selected is part 2 (head).

Table 5-17: summarized results of Image Fusion

Part	Appearance	GEI	CGEI	GHGI	CGHGI	Part	Appearance	GEI	CGEI	GHGI	CGHGI
1	Normal	**99.18**	97.81	**98.32**	98.43	8	Normal	99.02	97.30	97.88	98.12
	Bag	72.10	83.39	**92.20**	92.24		Bag	59.13	75.63	88.13	87.93
	Coat	55.56	78.88	87.30	87.50		Coat	69.67	82.09	**88.64**	**88.79**
	Mixed	75.61	86.69	**92.61**	**92.72**		Mixed	75.94	85.01	91.55	91.61
2	Normal	99.10	**98.20**	98.08	98.16	9	Normal	98.90	96.71	97.41	97.49
	Bag	73.82	**83.54**	92.16	**92.48**		Bag	72.53	76.25	88.13	88.28
	Coat	53.06	74.06	85.62	85.46		Coat	**83.66**	**87.46**	87.85	88.32
	Mixed	75.33	85.27	91.95	92.03		Mixed	**85.03**	**86.81**	91.13	91.37
3	Normal	99.14	97.92	**98.32**	98.39	10	Normal	98.75	96.59	97.26	97.37
	Bag	66.50	82.21	91.03	91.07		Bag	70.77	74.49	87.62	87.34
	Coat	57.01	77.00	86.21	86.36		Coat	82.33	86.56	87.07	87.74
	Mixed	74.22	85.71	91.85	91.94		Mixed	83.95	85.88	90.65	90.82
4	Normal	99.14	97.81	98.20	98.35	11	Normal	**99.18**	98.00	98.24	98.47
	Bag	66.93	81.54	91.34	90.71		Bag	67.87	81.54	91.46	91.38
	Coat	57.88	77.23	86.40	86.79		Coat	57.88	76.18	87.46	87.46
	Mixed	74.65	85.53	91.98	91.95		Mixed	74.97	85.24	92.39	92.44
5	Normal	99.14	97.73	98.24	98.35	12	Normal	99.10	97.73	97.96	98.16
	Bag	71.87	83.03	91.58	91.30		Bag	68.57	80.56	91.14	91.18
	Coat	59.21	79.55	87.30	87.30		Coat	60.62	76.68	87.74	87.89
	Mixed	76.74	86.77	92.37	92.32		Mixed	76.10	84.99	92.28	92.41
6	Normal	99.10	97.77	98.20	98.32	13	Normal	98.98	97.73	97.45	97.69
	Bag	70.96	83.03	91.22	91.34		Bag	**79.74**	81.82	91.85	91.81
	Coat	58.03	79.11	86.99	87.15		Coat	63.17	73.51	85.85	86.13
	Mixed	76.03	86.64	92.14	92.27		Mixed	80.63	84.35	91.72	91.88
7	Normal	99.14	97.69	98.28	**98.51**	14	Normal	98.98	97.73	97.45	97.49
	Bag	59.01	76.25	88.83	88.99		Bag	78.10	81.07	91.61	91.38
	Coat	64.66	80.88	87.70	88.24		Coat	60.89	71.94	84.84	85.31
	Mixed	74.27	84.94	91.60	91.91		Mixed	79.32	83.58	91.30	91.39

The best four fusions for gait representations are

- GEI: 85.03% at fusion 9, 83.95% at fusion 10, 80.63% at fusion 13 and 79.32% at fusion 14
- CGI: 86.81% at fusion 9, 86.77% at fusion 5, 86.69% at fusion 1 and 86.64% at fusion 6
- GHGI: 92.61% at fusion 1, 92.39% at fusion 11, 92.37% at fusion 5 and 92.28% at fusion 12
- CGHGI: 92.72% at fusion 1, 92.44% at fusion 11, 92.41% at fusion 12 and 92.32% at fusion 5

GEI has the lowest fusion classification rates when compared with other gait representations. Only six GEI fusions have a higher classification rate than single selected parts. Fusion 9 and 12 have approximately 3% higher classification rate than the single selected part.

All CGI fusions had higher classification rates than a single selected part, even the lowest classification rate of 83.58% at fusion 12. Some fusions made classification rates increase more than five percent. At fusions 11 and 12 classification rates are increased by 9.78% and 8.11%, respectively.

GHGI and CGHGI at fusions 1-6, which fuse part 1 with another part, have lower classification rate than single part 1 except CGHGI at fusion 1, while GHGI and CGHGI at fusions 7-14 have better classification rate than single selected parts.

If part 1 (full body) is excluded from this experiment, the best classification rate for each representation is 85.03% GEI at fusion 9, 86.81% CGI at fusion 9, 92.39% GHGI at fusion 11 and 92.44% CGHGI at fusion 11. These GEI and CGI fusions have a higher classification rate than the best classification rate of single part GEI and CGI experiment. While the best classification rate of single part GHGI and CGHCI are higher than GHGI and CGHGI fusion as it can be seen in Table 5.6. The rest of the fusions usually have higher classification rates than individual selected parts, except GEI at fusions 13 and 14. Especially CGI fusion 11 and 12 where the classification rate increased by more than 8% compared with a single selected part. While GEI fusion 12 has the most classification rate increases it had only increased by 3% when compared with the single selected part in Table 5.6. Classification rates for all GHGI and CGHGI fusions are higher than 90%. All CGI fusions have classification rates higher than 83%,

5.4 Multi-duplication part (MRD)

From Section 5.3, the majority of the results have shown that the best single selected part is better than fusion 1 to 6 image fusion except GEI fusion 2 and 4, CGI all fusion 1 to 6 and CGHGI fusion 1. While fusions 7 to 14 CGI, GHGI and CGHGI have better classification rate than the single selected part. This means image fusion is suitable for gait recognition in some conditions.

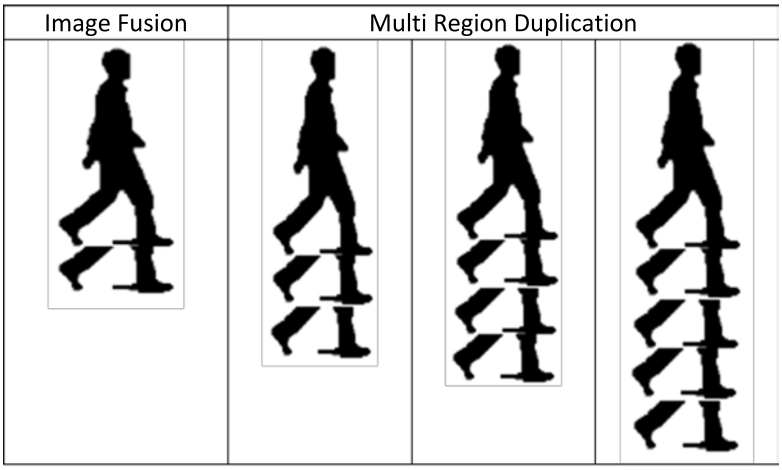


Figure 5-5: Multi Region Duplication Example

If fusions 1-6 are considered, all fusions have some duplicated part because part 1 already has a full body silhouette. When part 1 is fused with another part, the image fusion representation has the duplicated silhouette of that part. Part 11 of both GEI and CGI has a better classification rate than the full body as it can be seen in Table 5.6. From this point of view, the fusion ratio of 1:1 may not be the best fusion because each part's contribution to the gait recognition may not be the same. An assumption is that the duplicated part may increase the classification rate in some gait representation and fusion. This motivated a new gait representation which concatenates two selected parts with a different ratio. This experiment used the same fusion as in section 5.3, nevertheless, the fusion ratios are 1:2, 1:3 and 1:4 as they are shown in Figure 5.5.

5.4.1 Evaluation

This experiment focused on the number of duplicated parts. The number of the first part was fixed to one while the number of second part was consequently increased from two to four. This experiment used the same parameters as in section 5.3. The summarized results are presented in Table 5.18.

Table 5-18: Summarized Results of Multi Region Duplication

Fusion	GEI			CGI			GHGI			CGHGI		
	1:2	1:3	1:4	1:2	1:3	1:4	1:2	1:3	1:4	1:2	1:3	1:4
1	76.37	76.87	**77.52**	86.69	87.13	88.78	92.59	92.48	92.29	92.76	92.40	92.40
2	75.91	76.21	75.94	83.79	83.05	83.70	91.65	90.84	90.39	91.65	90.83	90.62
3	73.93	73.63	73.37	84.15	83.87	83.31	91.61	91.26	90.87	91.52	91.11	90.88
4	74.54	74.53	74.46	83.95	83.66	82.71	91.50	91.09	90.82	91.35	90.90	90.91
5	78.06	78.91	**79.41**	87.30	87.79	88.13	91.95	91.81	91.48	92.15	91.72	91.51
6	77.17	77.90	**78.33**	86.71	87.08	87.51	91.84	91.39	90.87	91.85	91.22	91.03
7	73.29	72.47	72.26	83.30	82.76	82.81	90.95	90.44	90.28	91.13	90.20	90.09
8	74.65	74.03	73.63	82.91	82.45	81.62	90.90	90.33	89.92	90.87	89.97	89.93
9	84.68	84.68	84.51	87.73	87.60	87.62	90.52	89.67	89.17	90.67	89.38	89.42
10	83.75	83.67	83.41	86.78	86.73	86.64	89.68	88.73	88.04	89.56	88.45	88.30
11	74.46	74.03	73.50	84.10	83.75	83.70	92.06	91.50	91.05	92.11	91.12	91.04
12	75.55	75.47	75.09	83.65	83.34	82.71	91.78	91.21	90.84	91.89	91.05	91.07
13	82.25	82.89	**83.41**	86.31	87.28	87.77	91.46	91.14	90.78	91.75	90.90	90.83
14	80.79	81.60	**82.00**	85.21	86.10	86.48	91.11	90.44	89.93	91.11	90.40	90.13

In Table 5.18, most results indicate that the duplicated parts did not improve classification rate. Conversely, the classification rate slightly dropped when the ratio increased. Except for GEI and CGI at fusions 1, 5, 6, 13 and 14, classification rates decreased when the ratio increased. Interestingly, these fusions include parts 11 (lower knee) and/or 12 (ankle).

5.4.2 Discussion

MRD is not the best answer for improving gait classification rate, as it can be seen in Table 5.18. Almost all results show decreased classification rates when the ratio was increased. If the results are compared with results demonstrated in Section 5.3 in which two selected parts are fused with a one to one ratio, the image fusion archive better classification rate than MRD in most cases. Nonetheless, there are some GEI and CGI fusions including 1, 5, 6, 13 and 14 which have better results. Almost all of these fusions employed parts 11 and 12 in order to induce higher classification rates. This may imply the potential of lower knee and ankle region in gait recognition with GEI and CGI representation.

5.5 View variations

There are two view angle challenges including view angle classification and cross view gait recognition. The view angle classification uses the same framework as Chapter 3 and 4 as it can be seen in Figure 3.10. While the cross view gait recognition uses the same gait recognition system as in Figure 3.1. Gait features are extracted from gait compact image and optimal feature map which is still created from each view angle component by PCA. The personal model is trained and tested by SVM. The main difference in cross view is the optimal feature map selection. In an identical view angle, the probe sample is exactly applied with the optimal feature map from the same view angle of the probe sample. In cross view, the view angle of the probe is unknown, however, the view angle of the gallery model is known. Thus unknown probe sample is applied by the optimal feature map from the same view angle with the gallery model. For example, models are generated from 90° gallery samples. An unknown probe sample is applied with the optimal feature map which is generated from 90° gallery sample in training. Next, the extracted feature is tested with 90° models by SVM prediction.

5.5.1 Evaluation

The view angle classification with partial body parts was tested with twelve different body parts including full body as it is shown in Table 5.1. Results which are averaged from eleven view angles are shown in Table 5.19.

Table 5-19: View angle classification by partial body

Gait Representation		Part											
		1	2	3	4	5	6	7	8	9	10	11	12
Basic	GEI	88.07	52.13	56.10	62.89	57.77	57.68	60.51	58.40	87.03	88.17	**94.38**	91.97
	GEnI	89.92	54.04	58.93	63.53	60.25	59.98	63.82	61.60	89.00	90.90	**94.21**	90.87
	GGI	91.69	59.47	65.46	71.62	66.84	66.27	66.61	63.45	90.48	90.26	**95.82**	93.91
	GGEnI	95.04	64.41	68.48	72.92	69.54	69.23	71.33	69.74	94.44	94.50	**96.41**	94.61
CGI	GEI	89.56	52.65	56.27	62.57	57.57	58.14	61.52	58.58	88.44	89.39	**94.43**	91.41
	GEnI	90.86	55.14	59.51	64.27	60.75	60.72	65.11	61.71	90.52	91.35	**94.30**	90.42
	GGI	92.60	58.00	64.56	70.16	65.91	65.39	67.48	63.10	91.64	91.94	**96.21**	93.83
	GGEnI	95.25	64.97	69.51	73.54	70.62	70.27	71.55	69.89	94.94	95.23	**96.53**	93.99
GHGI	GEI	95.77	58.19	58.65	66.37	63.94	64.68	68.95	67.72	95.73	95.91	**96.19**	94.12
	GEnI	95.83	57.54	57.97	65.52	62.58	62.85	67.33	66.77	95.70	96.00	**96.12**	93.99
	GGI	97.92	66.09	69.12	79.15	75.31	75.12	78.45	79.51	97.91	**98.05**	97.96	96.84
	GGEnI	97.82	66.01	68.81	78.64	74.63	75.17	78.30	79.25	97.79	97.94	**97.96**	96.84
CGHGI	GEI	95.38	60.01	60.98	67.78	62.96	64.06	67.29	66.07	94.91	95.07	**95.98**	94.04
	GEnI	95.42	59.16	60.03	66.77	62.19	62.44	66.38	65.48	95.10	95.38	**96.12**	93.72
	GGI	97.49	72.77	73.48	80.76	75.55	76.12	78.53	77.72	97.31	97.45	**97.61**	96.50
	GGEnI	97.30	72.05	73.01	80.37	75.80	76.35	78.41	78.58	97.27	97.47	**97.49**	96.50

From the results in Table 5.19, the best view angle classification rate was 98.05% GHGI-GGI of part 10 (lower hip) followed by 97.96% GHGI-GGI of part 11 and GHGI-GGEnI of part 11 (lower knee). The body part, which gives the best view angle classification, was part 11 or lower knee which had the highest classification rate for almost all gait representations except GHGI-GGI.

The cross view gait recognition used four normal walking datasets as gallery samples. The rest including two datasets from each appearance are used as probe samples. Two gait representations were tested under this experiment. First was GEI that was the basic gait compact image. The second was GHGI which applied HOG technique on GEI. GHGI was chosen because it had the best classification rate as presented in Chapter 4. HOG parameters were set as cell size 2x2, block size 2x2 and bin 18. Results are shown in Table 5.20 and 5.21.

The results indicate that GHGI enormously increased the view angle classification rate when the gallery sample was a fixed view angle and the probe set was all view angles. When the gap between the probe view and gallery view increased, the classification rate decreased. When keep increasing the gap value approximately over 90 degree, the classification rate increased again.

A single part from the fourteen divided parts was also tested in this experiment. Results of the GHGI single part are shown in Table 5.22. In this table, each gallery view was tested by mixed appearances and mixed view angle probe sets. The highest CCRs are respectively highlighted by different colours following first-yellow, second-blue, third-pink, forth-orange and fifth-green.

From the result, part 1 or full body had the best average classification rate of 74.0%. Surprisingly, body parts involving parts 5, 6 and 7 which had the problem with appearance changes and normally had a low classification rate, received a higher rate than 61.7%. Parts 11 and 12 which captured most movement at the lower part had very low classification rate in this test. This is because parts 11 and 12 silhouettes were changed much more than other parts when the camera view angle was changed.

Table 5-20: GEI cross view recognition

			Probe										
		Angle	0	18	36	54	72	90	108	126	144	162	180
Gallery	Normal	0	99.6	81.5	33.6	12.9	3.9	3.9	4.3	7.8	19.8	40.1	64.2
		18	84.5	100.0	90.1	46.6	25.0	19.0	24.1	32.3	42.2	66.4	57.8
		36	56.5	92.7	99.6	85.8	52.6	33.6	39.2	49.6	65.9	71.1	50.9
		54	22.4	44.8	86.6	98.7	92.2	72.0	79.3	86.6	77.6	44.8	22.8
		72	10.3	18.5	44.4	94.0	98.7	98.3	96.6	82.8	47.0	22.4	8.6
		90	9.1	13.8	29.7	84.1	98.3	99.1	99.6	79.3	41.4	20.3	10.3
		108	12.1	16.4	35.3	86.2	97.4	98.3	99.1	93.1	59.5	27.2	17.7
		126	12.5	26.7	56.5	89.7	90.5	86.6	97.8	99.1	92.2	47.0	20.7
		144	19.8	43.1	72.8	81.5	50.0	57.8	74.6	94.8	98.3	82.8	35.3
		162	45.3	76.3	78.4	53.9	34.9	30.2	31.9	51.3	80.2	98.7	85.3
		180	70.7	65.1	52.6	32.3	25.9	21.6	20.7	30.6	40.1	86.6	99.1
	Bag	0	75.4	56.0	29.3	10.3	5.2	4.3	5.2	6.0	15.1	31.9	45.3
		18	50.0	70.7	53.0	25.4	13.8	13.4	13.4	17.7	19.0	37.9	31.5
		36	31.5	56.0	71.6	49.6	26.3	22.4	21.1	25.9	31.5	37.5	26.3
		54	10.8	22.0	44.4	65.9	56.9	41.4	47.0	51.3	40.5	28.9	12.1
		72	7.8	10.8	15.5	45.3	66.8	57.3	56.5	48.7	25.4	13.4	8.6
		90	7.3	9.5	11.6	34.1	53.9	65.5	65.1	43.5	19.4	10.8	6.5
		108	7.3	13.4	16.8	45.7	55.2	60.8	67.2	53.9	31.9	16.4	9.1
		126	7.3	15.1	28.9	47.0	46.1	46.1	54.7	69.0	51.7	28.0	10.3
		144	11.6	18.5	37.5	42.7	26.3	29.3	34.9	53.4	68.1	42.7	19.0
		162	24.6	46.1	47.4	33.6	22.0	21.1	25.4	30.2	44.4	71.6	48.3
		180	45.3	40.9	31.9	20.3	17.2	10.8	10.3	16.8	22.0	51.3	78.0
	Coat	0	47.0	39.2	31.9	18.1	10.8	7.3	9.5	15.1	22.0	29.7	33.2
		18	32.3	58.2	53.9	31.5	21.1	21.6	21.6	22.8	24.1	40.5	27.6
		36	20.3	43.1	55.2	52.2	35.3	28.4	28.9	29.3	29.7	33.6	19.0
		54	9.9	18.1	41.4	59.9	62.1	50.4	50.0	43.5	33.6	22.4	14.2
		72	7.8	8.6	15.1	36.2	57.8	56.9	47.4	32.3	22.4	12.9	6.9
		90	7.8	9.1	9.1	29.7	48.3	57.3	45.7	23.7	13.8	10.3	8.2
		108	8.6	12.5	17.2	35.8	49.1	57.3	54.3	37.5	23.3	15.9	12.5
		126	6.5	11.6	25.0	40.9	43.5	44.0	47.8	53.4	38.4	21.6	9.5
		144	9.9	22.0	31.5	40.9	28.0	30.6	34.1	46.6	51.7	31.9	15.5
		162	14.7	30.6	39.7	34.9	25.0	24.6	25.4	33.2	36.2	51.7	31.9
		180	17.7	28.0	25.0	19.4	16.8	14.2	13.8	13.8	14.2	34.5	48.3
	Mixed Appearance	0	74.0	58.9	31.6	13.8	6.6	5.2	6.3	9.6	19.0	33.9	47.6
		18	55.6	76.3	65.7	34.5	20.0	18.0	19.7	24.3	28.4	48.3	38.9
		36	36.1	63.9	75.4	62.5	38.1	28.2	29.7	34.9	42.4	47.4	32.0
		54	14.4	28.3	57.5	74.9	70.4	54.6	58.8	60.5	50.6	32.0	16.4
		72	8.6	12.6	25.0	58.5	74.4	70.8	66.8	54.6	31.6	16.2	8.0
		90	8.0	10.8	16.8	49.3	66.8	74.0	70.1	48.9	24.9	13.8	8.3
		108	9.3	14.1	23.1	55.9	67.2	72.1	73.6	61.5	38.2	19.8	13.1
		126	8.8	17.8	36.8	59.2	60.1	58.9	66.8	73.9	60.8	32.2	13.5
		144	13.8	27.9	47.3	55.0	34.8	39.2	47.8	64.9	72.7	52.4	23.3
		162	28.2	51.0	55.2	40.8	27.3	25.3	27.6	38.2	53.6	74.0	55.2
		180	44.5	44.7	36.5	24.0	20.0	15.5	14.9	20.4	25.4	57.5	75.1

Table 5-21: GHGI cross view recognition

			0	18	36	54	72	90	108	126	144	162	180
Gallery	Normal	0	96.1	91.8	82.8	65.9	52.6	48.7	53.9	62.5	72.4	81.0	87.1
		18	91.4	99.1	94.4	78.9	59.5	56.9	59.9	63.4	71.1	87.1	85.3
		36	89.7	97.4	99.6	97.0	84.9	76.3	78.9	85.3	90.5	92.2	87.9
		54	67.2	80.2	96.1	98.7	97.4	96.1	96.1	95.7	92.7	89.7	86.2
		72	53.4	53.0	78.9	97.8	98.7	98.7	97.8	95.7	84.5	78.0	72.8
		90	49.6	49.6	75.0	96.1	98.3	98.7	98.7	96.6	84.1	75.0	68.5
		108	54.7	54.3	77.2	96.6	97.0	98.7	98.7	98.7	92.2	79.3	75.9
		126	66.8	72.4	89.2	95.7	96.1	96.1	97.8	98.7	96.6	91.4	84.5
		144	83.6	84.9	91.4	93.5	91.8	90.9	93.5	97.4	98.3	94.4	91.4
		162	86.6	88.8	90.1	90.1	84.5	84.1	87.1	89.2	96.1	99.1	95.3
		180	94.8	89.2	89.2	86.6	76.7	75.0	77.2	83.2	90.5	95.7	97.0
	Bag	0	88.8	84.9	78.9	62.5	45.7	40.5	38.8	50.9	59.9	75.9	81.0
		18	68.1	91.8	87.9	67.7	43.5	40.5	43.5	53.4	66.4	73.3	66.4
		36	48.7	79.3	92.7	85.3	61.2	52.6	56.9	63.8	68.1	68.1	64.7
		54	34.1	49.1	81.5	91.8	89.2	84.1	83.2	81.5	69.8	62.9	57.8
		72	30.2	34.1	52.6	86.6	95.3	91.8	88.4	77.2	62.5	49.6	45.3
		90	29.7	32.3	47.0	83.2	92.2	95.3	93.1	82.3	62.5	48.7	46.1
		108	31.9	32.8	50.0	82.8	92.7	94.4	96.1	88.8	69.4	54.7	48.7
		126	37.5	43.1	64.7	81.0	84.5	81.9	91.4	93.1	82.8	74.1	60.8
		144	44.0	56.5	69.4	79.3	75.9	73.7	78.9	86.6	89.2	81.0	71.1
		162	50.9	67.7	71.1	69.8	67.2	59.9	63.4	74.1	78.9	88.8	77.6
		180	57.8	64.7	74.6	75.0	62.1	56.0	61.6	68.5	73.3	82.8	85.8
	Coat	0	88.8	83.2	77.6	66.8	56.0	56.0	57.8	62.1	72.0	79.7	81.5
		18	80.2	90.1	88.4	69.8	52.2	46.6	51.3	57.8	68.1	78.0	74.1
		36	61.2	79.7	91.4	85.3	66.4	57.3	60.8	67.7	74.1	69.0	70.7
		54	44.4	49.1	78.9	90.5	87.5	84.9	81.9	78.0	73.3	65.5	61.6
		72	33.6	33.2	54.7	82.8	88.8	89.7	85.8	77.6	56.9	48.3	46.1
		90	35.8	31.9	46.6	76.3	85.8	87.9	87.1	70.7	56.9	45.3	46.6
		108	36.2	33.6	50.9	78.4	82.8	85.8	86.2	76.7	61.6	49.6	49.1
		126	48.3	47.0	67.2	80.2	79.3	80.2	83.2	85.8	81.5	68.5	62.9
		144	56.0	62.9	78.0	78.0	70.7	72.4	75.4	78.4	85.8	80.2	73.7
		162	58.6	70.3	72.8	74.1	65.5	67.7	64.7	68.5	77.6	85.3	75.0
		180	68.1	69.0	75.9	70.7	64.2	65.9	64.2	67.2	73.7	79.3	82.3
	Mixed Appearance	0	91.2	86.6	79.7	65.1	51.4	48.4	50.1	58.5	68.1	78.9	83.2
		18	79.9	93.7	90.2	72.1	51.7	48.0	51.6	58.2	68.5	79.5	75.3
		36	66.5	85.5	94.5	89.2	70.8	62.1	65.5	72.3	77.6	76.4	74.4
		54	48.6	59.5	85.5	93.7	91.4	88.4	87.1	85.1	78.6	72.7	68.5
		72	39.1	40.1	62.1	89.1	94.3	93.4	90.7	83.5	68.0	58.6	54.7
		90	38.4	37.9	56.2	85.2	92.1	94.0	93.0	83.2	67.8	56.3	53.7
		108	40.9	40.2	59.3	85.9	90.8	93.0	93.7	88.1	74.4	61.2	57.9
		126	50.9	54.2	73.7	85.6	86.6	86.1	90.8	92.5	86.9	78.0	69.4
		144	61.2	68.1	79.6	83.6	79.5	79.0	82.6	87.5	91.1	85.2	78.7
		162	65.4	75.6	78.0	78.0	72.4	70.5	71.7	77.3	84.2	91.1	82.6
		180	73.6	74.3	79.9	77.4	67.7	65.7	67.7	73.0	79.2	85.9	88.4

Table 5-22: cross view recognition by GHGI single part

		Gallery view											Average
		0	18	36	54	72	90	108	126	144	162	180	
part	1	69.2	69.9	75.9	78.1	70.3	68.9	71.4	77.7	79.6	77.0	75.7	74.0
	2	52.8	47.0	55.1	63.8	65.6	65.0	65.7	69.1	68.0	64.6	62.3	61.7
	3	56.1	51.0	56.2	61.1	55.0	51.9	57.4	61.9	64.0	62.1	58.4	57.7
	4	64.0	57.1	65.2	70.1	67.8	66.5	68.8	73.4	75.0	72.2	69.5	68.1
	5	61.2	59.1	64.4	67.7	60.7	60.6	64.0	67.7	70.3	66.0	63.8	64.1
	6	61.3	61.1	66.0	69.0	62.9	62.1	64.9	68.4	70.8	66.7	64.8	65.3
	7	65.2	66.4	70.4	71.8	66.0	65.0	66.6	71.6	73.8	71.4	68.8	68.8
	8	58.0	57.1	64.2	64.6	58.6	56.3	61.4	64.0	66.2	64.7	63.1	61.7
	9	57.0	56.3	66.3	70.1	61.7	58.4	61.9	66.5	66.8	65.1	65.8	63.3
	10	54.0	53.3	63.4	67.8	59.7	56.7	59.2	63.6	63.7	62.1	63.5	60.6
	11	39.3	40.6	49.5	55.4	49.5	47.8	48.8	50.9	49.0	44.7	49.2	47.7
	12	39.6	40.6	49.1	54.9	48.0	47.2	48.6	51.6	50.3	44.9	48.8	47.6

5.5.2 Discussion

In the view angle classification experiment, many body parts show the potential for view angle classification. From the results in Table 5.19, all lower body parts 9 to 12 have a higher classification rate than 90%. These parts have very similar classification rate with that of the whole body or part 1, especially part 11 always has a higher classification rate than the whole body. This means lower body part is very important for view angle classification. If lower body is obstructed, part 4 (upper chest) is the best part for view angle classification. The classification rate of the best upper part is 80.76% CGHGI-GGI.

The cross view gait recognition experiment has two challenges to deal with cross view recognition and appearance changes. All experiments train personal models with four normal walking datasets. The remaining datasets are used as a probe sample. During the training phase, each input uses the view optimal feature map calculated from the same view angle of training samples. During the testing phase, each sample feature is extracted by the optimal feature map from the same view with a model in the database. The testing sample may or may not have the same view as the model in the database. Thus the classification rate may dramatically drop when compared with gait recognition by the identical view. When the view gap between a testing sample view and a model view increases (but not more than 90°), the classification rate decreases. When the gap value is greater than 90°, and the gap value increases, the classification rate increases at the same time. The same with gait recognition by the identical view, when appearance change is taken into account, the classification rate drops as it can be seen in Table 5.20 and 5.21.

If the results of GEI and GHGI are compared, HOG technique has greatly improved the classification rate for all view angles. This means that the GHGI representation is more robust on appearance change and cross view recognition.

For partial body test, full body has the best performance. Body parts involving parts 4, 5, 6 and 7 are more robust than lower body and head parts which have good performance on personal recognition by an identical view. This is because the appearance of body parts 4, 5, 6, and 7 does not change much when the view angle is changed.

5.6 Summary

There are four main experiments conducted in this Chapter, which are a single part, part score fusion (PSF), part image fusion (PIF) and multi region duplication in gait recognition. All experiments are trained and are tested by GEI, CGI, GHGI and CGHGI representations. Summarized results are shown in Table 5.23 and 5.24.

The single part experiment shows a classification rate of twelve parts, including the full body. The best part which has the highest classification rate is CGHGI part 1 or full body (92.71%). However, the best part for GEI and CGI is part 11 or lower knee. If averaging each part's results, there are seven parts which have classification rates higher than 80%. These include part1-full body, part2-head, part 4-head to chest, part 9-limb, part 10-lower hip, part 11-lower knee and part 12-ankle. The rest of the parts are badly affected by carrying a bag and a wearing coat in CASIA dataset B. Although their classification rate improves when applying HOG techniques, as seen from GHGI and CGHGI classification rate.

Table 5-23: Summarized single part gait classification rate

Representation	Part											
	1	2	3	4	5	6	7	8	9	10	11	12
GEI	74.45	81.18	65.70	72.90	56.10	62.92	61.75	55.51	68.77	69.87	**82.16**	80.63
CGI	81.08	78.98	66.61	74.59	59.04	68.48	68.02	61.66	75.46	76.88	**84.15**	82.71
GHGI	**92.65**	86.02	78.74	87.36	82.24	83.10	84.99	82.64	90.13	89.63	88.17	87.42
CGHGI	**92.71**	85.72	78.50	87.38	82.07	83.02	84.90	82.17	89.89	89.39	87.98	87.34

Table 5-24: Summarized part fusion gait classification rate

Fusion	Part Score Fusion				Part Image Fusion (1:1)				Multi Region Duplication (1:4)			
	GEI	CGEI	GHGI	CGHGI	GEI	CGEI	GHGI	CGHGI	GEI	CGEI	GHGI	CGHGI
1	**83.59**	85.25	91.99	92.05	75.61	86.69	**92.61**	**92.72**	77.52	88.78	92.29	92.40
2	**77.44**	78.66	**92.35**	**92.39**	75.33	**85.27**	91.95	92.03	75.94	83.70	90.39	90.62
3	**74.36**	79.91	**92.35**	**92.42**	74.22	**85.71**	91.85	91.94	73.37	83.31	90.87	90.88
4	**75.48**	81.06	**92.50**	**92.39**	74.65	**85.53**	91.98	91.95	74.46	82.71	90.82	90.91
5	**83.71**	86.56	91.94	91.70	76.74	86.77	**92.37**	**92.32**	79.41	88.13	91.48	91.51
6	**83.18**	85.51	91.29	91.13	76.03	86.64	**92.14**	**92.27**	78.33	87.51	90.87	91.03
7	**80.59**	84.18	**91.81**	91.76	74.27	**84.94**	91.60	**91.91**	72.26	82.81	90.28	90.09
8	**80.41**	84.49	**91.97**	**92.01**	75.94	**85.01**	91.55	91.61	73.63	81.62	89.92	89.93
9	**85.72**	86.19	**91.35**	91.23	85.03	86.81	91.13	**91.37**	84.51	87.62	89.17	89.42
10	**85.12**	85.36	**90.97**	**90.90**	83.95	85.88	90.65	90.82	83.41	86.64	88.04	88.30
11	**76.53**	80.26	**92.58**	**92.55**	74.97	**85.24**	92.39	92.44	73.50	83.70	91.05	91.04
12	**77.01**	81.08	**92.84**	**92.80**	76.10	**84.99**	92.28	92.41	75.09	82.71	90.84	91.07
13	82.52	84.70	**91.89**	**91.90**	80.63	84.35	91.72	91.88	**83.41**	87.77	90.78	90.83
14	81.69	83.96	**91.50**	**91.39**	79.32	83.58	91.30	91.39	**82.00**	86.48	89.93	90.13

Part fusion experiments which recognize a person by two selected parts can be divided into three different experiments: part score fusion (PSF), part image fusion (PIF), and multi region duplication (MRD). The part score fusion experiment separately generates each part model and averages their scores together in the recognition stage. The highest scoring personal model is chosen as the recognition result. The experiments of image fusion and multi region duplication, which generate one model per person, had fused two or more selected parts into a single image.

If all single part and part fusion experiments are considered together, the comparison between the classification rate of part fusion approach and the best classification rate of the single selected part is demonstrated in Table 5.25. Positive values mean part fusion has a better classification rate than the best single selected part. Single part 1 or full body has better classification rate than part fusion in many fusions especially all GHGI and most CGHGI at fusions 1-6. CGI works well with PIF and MRD in which all fusions have better classification rates than the single selected part in each fusion.

If fusions 7-14 fused two selected parts together are being considered, almost all part fusion approaches have better classification rates except for GEI at fusions 7 and 8. Nonetheless, both fusions had better classification rates than GEI part 1 or full body. The best raising classification rate is 10.65% CGI-PIF at fusion 11 followed by 10.40% CGI-PIF at fusion 12.

Table 5-25: Classification rate comparison between fusion part and the best single selected part

Fusion	Part Score Fusion				Part Image Fusion (1:1)				Multi Region Duplication (1:4)			
	GEI	CGEI	GHGI	CGHGI	GEI	CGEI	GHGI	CGHGI	GEI	CGEI	GHGI	CGHGI
1	2.42	4.18	**-0.65**	**-0.65**	**-5.56**	5.61	**-0.04**	0.02	**-3.65**	7.70	**-0.35**	**-0.31**
2	2.99	**-2.41**	**-0.30**	**-0.32**	0.88	4.19	**-0.69**	**-0.67**	**1.49**	2.62	**-2.26**	**-2.08**
3	**-0.09**	**-1.17**	**-0.30**	**-0.28**	**-0.24**	4.63	**-0.80**	**-0.77**	**-1.08**	2.23	**-1.78**	**-1.82**
4	1.03	**-0.02**	**-0.14**	**-0.32**	0.20	4.45	**-0.67**	**-0.75**	0.01	1.63	**-1.83**	**-1.80**
5	1.55	2.41	**-0.71**	**-1.01**	**-5.42**	2.62	**-0.27**	**-0.39**	**-2.75**	3.98	**-1.16**	**-1.20**
6	2.55	2.79	**-1.36**	**-1.58**	**-4.60**	3.92	**-0.51**	**-0.44**	**-2.30**	4.80	**-1.78**	**-1.68**
7	**-0.59**	5.20	1.68	1.87	-6.91	5.96	1.48	2.02	**-8.92**	3.83	0.16	0.19
8	**-0.77**	5.51	2.34	2.62	-5.24	6.03	1.92	2.23	**-7.55**	2.64	0.29	0.54
9	3.56	2.05	3.19	3.26	2.87	2.66	2.96	3.39	2.35	3.47	1.01	1.44
10	3.95	2.65	3.55	3.56	2.77	3.17	3.23	3.48	2.24	3.92	0.61	0.96
11	3.63	5.66	2.46	2.66	2.07	10.65	2.26	2.54	0.60	9.11	0.93	1.15
12	4.11	6.49	3.21	3.41	3.19	10.40	2.65	3.03	2.19	8.11	1.21	1.68
13	0.36	0.56	3.72	3.92	-1.53	0.20	3.55	3.90	1.25	3.63	2.61	2.86
14	1.06	1.24	4.08	4.01	-1.30	0.87	3.88	4.01	1.37	3.77	2.51	2.75

The classification rate for part 1 or full body is 74.45% GEI, 81.08% CGI, 92.65% GHGI and 92.72% CGHGI. If section 4.2 experiments are included, the best classification rate for GHGI and CGHGI changes to 93.13% and 93.01%, respectively. All GEI fusions except PSFF fusion 3, PIFF fusions 3 and 7, and MRD fusions 3, 7, 8 and 10 have better classification rates than full body. All CGI fusion except PSF fusions 2, 3, 4 and 11 have better classification rates than full body. All GHGI and CGHGI fusions have a lower classification rate than single part 1 or full body. Nonetheless, all fusions except GHGI-MRD at fusion 14 have higher classification rates than 90%. All results show that the partial body and partial body fusion can be used as gait recognition when some body parts are obstructed by activities or carrying objects. It is worth to note that these results are based on CASIA dataset B.

The comparison of this study and other publications have been shown in Table 5.26 and 5.27. All methods use 4 normal walking datasets as gallery samples. All methods normally have higher CCR when they are tested with normal walking samples. The CCRs are lower when they are tested by different appearance samples. The proposed gait representation and framework have the outperform CCR comparing with the other publications.

Table 5-26: Comparison of average CCR over eleven view angles on CASIA dataset B

Method	Normal	Bag	Coat	Average
Masked-GEI CDA[106]	98.57	77.78	86.46	87.60
Deep CNN[74]	95.60	88.30	86.20	90.03
GEI_{JSM} + RM1[84]	97.20	91.20	63.30	83.90
GOFI [77]	98.00	90.00	64.00	84.00
AESI+ZNK [50]	**100.00**	93.10	81.30	91.47
TGLSTM [73]	86.10	87.80	85.20	86.37
CGI-GEI (D-3 Chapter 4)	**99.38**	81.10	64.97	81.82
GHGI-GEI (Chapter 4)	98.63	**92.30**	88.45	93.13
CGHGI-GEI (E-3 Chapter 4)	98.67	91.73	88.52	92.97
CGI-GEI MRD 1:4 fusion 2 (Chapter 5)	99.22	86.91	80.21	88.78
GHGI-GEI PSF fusion 12 (Chapter 5)	98.04	91.26	**89.22**	92.84
GHGI-GEI PIF fusion 2 (Chapter 5)	98.32	92.20	87.30	92.61
CGHGI-GEI PSF fusion 12 (Chapter 5)	97.94	91.09	**89.37**	92.80
CGHGI-GEI PIF fusion 2 (Chapter 5)	98.43	**92.24**	87.50	92.72

The lateral view or 90° is the popular view angle in gait research. The CCR comparison under this view is shown in Table 5.27. The proposed gait representations and framework have less CCR than the best CCR in case of normal walking and wearing a coat. Especially, the best CCR of wearing a coat testing has greatly higher than this study. In case of carrying a bag testing, this study has higher CCR than the best CCR in the other publications. And there are many combinations of gait representation and framework in this study which has the same level as the best average CCR in the other publication.

The second task is the View angle classification that is one of the gait challenges. The Gaussian technique is suitable to solve this problem. Entropy technique increases the appearance change robustness. GGEnI which combines both techniques has the best CCR comparing with GEI, GEnI and GGI. HOG technique also improves the CCR. The combination of Gaussian and HOG techniques greatly improve the CCR as it can be seen from GHGI-GGI results. Lastly, part 10 (lower hip) and part 11 (lower knee) is the best effective part of this experiment. GHGI-GGI part 10 is the best combination of gait representation and partial body on view angle classification.

Table 5-27: Comparison of lateral view CCR on CASIA dataset B

Method	Normal	Bag	Coat	Average
Deterministic learning[39]	98.40	93.50	90.30	94.07
SG[69]	98.40	86.70	**94.80**	93.30
Two-phase VI-MGR[91]	**100.00**	89.00	76.00	88.33
Persistence homology[80]	94.10	84.20	87.60	88.60
SD+GLPP[110]	98.80	70.10	89.29	86.06
VI-MGR[46]	98.39	75.89	91.96	88.75
Sparse Dictionary Learning[112]	98.40	86.70	**94.80**	93.30
Fusion(sum)[71]	96.00	94.00	92.00	94.00
GEI with bolt-on module [123]	98.40	77.40	93.10	89.70
SVIM with bolt-on module [123]	98.00	96.80	73.00	89.20
GHGI-GEI (Chapter 4)	98.71	95.69	89.01	94.47
CGHGI-GEI (Chapter 4)	98.71	95.69	88.79	94.40
GHGI-GEI head to chest (Chapter 5)	96.55	96.12	72.84	88.51
GHGI-GEI PSF fusion 4 (Chapter 5)	99.14	94.83	88.79	94.25
GHGI-GEI PSF fusion 8 (Chapter 5)	99.14	95.26	88.79	94.40
GHGI-GEI PSF fusion 12 (Chapter 5)	98.71	96.12	88.36	94.40
CGHGI-GEI PSF fusion 8 (Chapter 5)	98.99	95.11	89.66	94.59
CGHGI-GEI PSF fusion 12 (Chapter 5)	98.56	95.83	88.79	94.40
GHGI-GEI PIF fusion 13 (Chapter 5)	97.41	**97.41**	86.21	93.68
CGHGI-GEI PIF fusion 6 (Chapter 5)	98.71	96.98	88.36	**94.68**
CGHGI-GEI PIF fusion 8 (Chapter 5)	99.14	94.40	89.22	94.25
CGHGI-GEI PIF fusion 13 (Chapter 5)	96.98	87.07	93.97	92.67
GHGI-GEI MRD 1:4 fusion 1 (Chapter 5)	98.28	95.69	88.36	94.11
GHGI-GEI MRD 1:4 fusion 5 (Chapter 5)	98.71	96.12	87.07	93.97
GHGI-GEI MRD 1:4 fusion 13 (Chapter 5)	97.41	96.12	87.07	93.53
CGHGI-GEI MRD 1:4 fusion 1 (Chapter 5)	98.28	95.69	88.36	94.11
CGHGI-GEI MRD 1:4 fusion 5 (Chapter 5)	98.71	96.55	87.93	94.40
CGHGI-GEI MRD 1:4 fusion 13 (Chapter 5)	97.84	96.12	86.21	93.39

When the CCR results of proposed view angle classification are compared with results from other published works for CASIA dataset B, the summarized view angle classification rate is shown in Table 5.28. Bashir et al [124], Choudhury et al [91], and Verlekar and Correia [125] used four normal walking as the gallery set and the rest, two samples of normal walking, two of walking with a coat, and two of carrying a bag, are used as a probe set. Bashir et al [124] use only 60% of the subjects for training and the rest 40% subject for testing while Choudhury et al [91] and Verlekar and Correia [125] use all subjects in training and testing set. Heifeng [126] randomly divide all datasets into two groups. the training set group has 24 subjects and the rest go to the testing group. Velekar et al [127] use K-NN that is no training. Thus all databases are used for testing. This study uses four samples of the normal walking as the gallery set and the remaining as a probe set.

Table 5-28: View Classification Comparison (N-normal, B-bag and C-coat)

Method		View Angle											Mean	
		0	18	36	54	72	90	108	126	144	162	180		
SVM[1]	N	-	-	95	41	85	64	24	44	98	-	-	64.39	64.46
	B	-	-	94	50	81	61	23	42	97	-	-	63.79	
	C	-	-	96	42	79	63	28	51	98	-	-	65.2	
GP[1]	N	-	-	84	91	85	74	86	91	94	-	-	86.46	85.96
	B	-	-	84	91	85	74	86	91	94	-	-	86.46	
	C	-	-	83	89	85	69	83	93	94	-	-	84.97	
VI-MGR[3]	N	83	94	88	92	81	89	79	90	83	89	82	86.36	82.94
	B	79	85	80	89	78	72	70	85	79	84	75	79.64	
	C	80	87	85	90	80	79	75	88	81	86	80	82.82	
Phash[4]	N	91	90	70	92	96	95	94	96	95	95	95	91.73	86.73
	B	86	76	56	72	88	86	87	91	83	88	88	81.91	
	C	86	81	66	87	90	88	92	92	91	89	90	86.55	
Feet GTI[5]	N	98	99	98	99	98	97	95	98	96	97	99	97.64	97.48
	B	98	99	98	98	98	97	95	99	96	96	99	97.55	
	C	96	99	98	99	99	97	94	99	96	96	97	97.27	
GGI part 1	N	99.6	100.0	100.0	100.0	100.0	99.1	100.0	100.0	99.1	99.1	99.6	99.69	91.69
	B	84.5	79.7	95.7	90.1	88.8	68.5	68.5	94.8	87.9	87.1	83.6	84.48	
	C	90.9	96.6	96.1	93.5	89.2	65.9	95.7	92.2	92.7	94.0	93.1	90.91	
GGEnI part 1	N	99.6	100.0	100.0	100.0	100.0	100.0	99.6	100.0	99.1	99.1	99.1	99.69	95.04
	B	95.7	94.4	97.8	97.8	98.3	91.8	84.5	97.4	90.5	95.3	92.2	94.16	
	C	94.8	96.1	94.4	94.0	86.2	75.0	91.8	96.6	85.8	94.4	94.8	91.26	
GGI part 11	N	99.6	100.0	100.0	100.0	100.0	98.7	98.3	100.0	98.7	99.1	98.7	99.37	95.82
	B	84.9	95.3	94.0	95.3	90.5	92.7	90.5	97.4	89.7	92.7	90.1	92.08	
	C	94.4	96.6	99.1	98.7	94.8	97.0	93.5	100.0	96.6	93.5	91.8	96.00	
GGEnI part 11	N	99.6	99.1	100.0	100.0	100.0	98.3	98.3	100.0	98.7	98.7	100.0	99.33	96.41
	B	94.8	92.7	94.0	97.0	94.4	94.0	90.9	96.6	91.8	91.8	94.8	93.89	
	C	96.1	97.0	96.6	98.7	94.4	97.0	97.4	97.0	95.3	92.7	94.0	96.00	
GHGI-GGI part 1	N	100.0	100.0	100.0	100.0	100.0	98.7	99.6	100.0	100.0	100.0	100.0	99.84	97.92
	B	100.0	99.6	98.7	98.3	95.7	97.0	93.1	98.3	96.1	95.3	96.1	97.10	
	C	97.4	98.7	98.3	97.8	96.1	94.8	98.7	98.3	96.1	94.8	94.0	96.83	
GHGI-GGEnI part 1	N	99.6	100.0	100.0	100.0	100.0	99.1	99.1	100.0	100.0	100.0	100.0	99.80	97.82
	B	98.7	99.6	98.3	98.7	94.8	97.4	94.4	98.3	95.3	95.3	97.4	97.10	
	C	97.0	97.8	98.3	97.4	96.1	93.5	97.8	98.7	96.1	94.8	94.4	96.55	
GHGI-GGI part 10	N	100.0	100.0	100.0	100.0	100.0	98.3	99.1	100.0	100.0	100.0	100.0	99.76	98.05
	B	97.8	98.7	99.1	99.1	96.6	94.4	96.1	98.7	96.1	94.8	97.0	97.14	
	C	98.3	97.4	99.6	98.7	96.1	95.3	98.3	99.1	96.6	95.7	94.8	97.26	
GHGI-GGEnI part 11	N	100.0	100.0	100.0	98.7	99.1	96.6	97.8	99.1	97.8	97.8	100.0	98.82	97.96
	B	97.0	98.3	98.7	97.8	99.1	95.3	97.8	98.7	96.1	95.3	96.1	97.30	
	C	98.3	97.0	99.6	99.1	98.7	97.4	98.3	99.1	96.1	96.6	95.3	97.77	

Cross view gait recognition identifies individual probe samples with the gallery sample from the different view angles. GHGI is the best gait representation and full body is the most effective part for this problem. The comparison between GHGI-GEI full body for view angle classification and other published research are shown in Table 5.29 and 5.30. As it can be seen, GHGI-GEI has explicitly highest classification rate in all appearances tests. This is not only the benefit of the HOG technique but the optimal feature selection also the main reason in this experiment.

Table 5-29: The comparison of cross view recognition

Method	Normal	Bag	Coat	Average
GEI-NNC [102]	28.44	14.91	8.82	17.37
GSP-CRC[128]	21.9	15.3	11.9	16.4
SG [69]	24.85	19.48	20.36	21.57
PFM[129]	41.88	29.55	41.78	37.74
GEI	56.82	33.55	29.50	39.96
GHGI-GEI	84.99	68.07	68.87	73.97

Table 5-30: Cross view classification rate when the model is trained by the lateral view

NM-Normal, BG-Bag, CL-Coat and AVG-Average

Probe Angle	Baseline[3]				SG[36]				PFM[129]				GHGI-GEI			
	NM	CL	BG	AVG	NM	CL	BG	AVG	NM	CL	BG	AVG	NM	CL	BG	AVG
0	0.4	0.4	1.2	0.7	1.6	0.8	2.1	1.5	0.80	0.80	2.40	1.33	49.57	35.78	29.74	38.36
18	2.4	2.8	2.4	2.5	1.2	0.8	1.6	1.2	4.40	1.60	2.40	2.80	49.57	31.90	32.33	37.93
36	4.8	5.2	4	4.7	2.4	1.6	2.8	2.3	18.10	13.30	25.00	18.80	75.00	46.55	46.98	56.18
54	17.7	8.5	6	10.7	11.7	8.1	8.5	9.4	67.70	49.20	71.80	62.90	96.12	76.29	83.19	85.20
72	82.3	42.3	20.6	48.4	86.7	71.8	70.9	76.5	80.20	59.30	79.40	72.97	98.28	85.78	92.24	92.10
90	97.6	52	32.7	60.7	96.8	85.5	83.1	88.5	99.60	82.30	100.0	93.97	98.71	87.93	95.26	93.97
108	82.3	31.9	16.5	43.6	62.1	37.9	39.1	46.4	97.20	63.30	87.10	82.53	98.71	87.07	93.10	92.96
126	15.3	9.7	6	10.3	4.8	3.3	8.1	5.4	76.60	41.10	69.80	62.50	96.55	70.69	82.33	83.19
144	5.2	6	3.6	4.9	4.1	2.9	4.9	3.9	12.50	10.90	18.50	13.97	84.05	56.90	62.50	67.82
162	3.6	3.2	3.2	3.3	1.6	0.8	2.4	1.6	2.40	2.40	2.40	2.40	75.00	45.26	48.71	56.32
180	1.2	2	0.8	1.3	0.4	0.8	0.5	0.6	1.20	0.80	0.80	0.93	68.53	46.55	46.12	53.74
	Total average = 17.4				Total average = 21.6				Total average = 37.74				Total average = 68.89			

From Chapter 3 to 5, the study is experimental on CASIA dataset B which has 3 appearances and 11 view angles variations. This dataset is captured gait images sequences from 124 subjects. The next Chapter uses the large population dataset called OU-ISIR Large Population dataset with Bag (OU-LP-Bag) that is currently the largest dataset with a carrying object variation.

Chapter 6 Gait Recognition with a large population dataset

Chapters 3 to 5 used CASIA dataset B as gait database for evaluation. This Chapter extends the evaluation to the OU-ISIR Large population dataset with bag, which is recently made available to the gait recognition community [99]. The example of this dataset is shown in Figure 6.1. A general framework for this Chapter is the same as that in Chapter 5 as shown in Figure 5.1. Four gait representations namely GEI, CGI, GHGI and CGHGI are selected as input to the classifier. One representative image per person is applied with the optimal feature map calculated by PCA. This gait feature is used to train personal models by SVM in the training phase. In the same way, reduced data is tested with all personal models in the testing phase. Finally, the highest score model is chosen as the result. This Chapter is divided into four sections, introduction to OU-ISIR large population dataset with bag, partial body gait recognition, partial body fusion gait recognition, and summary.

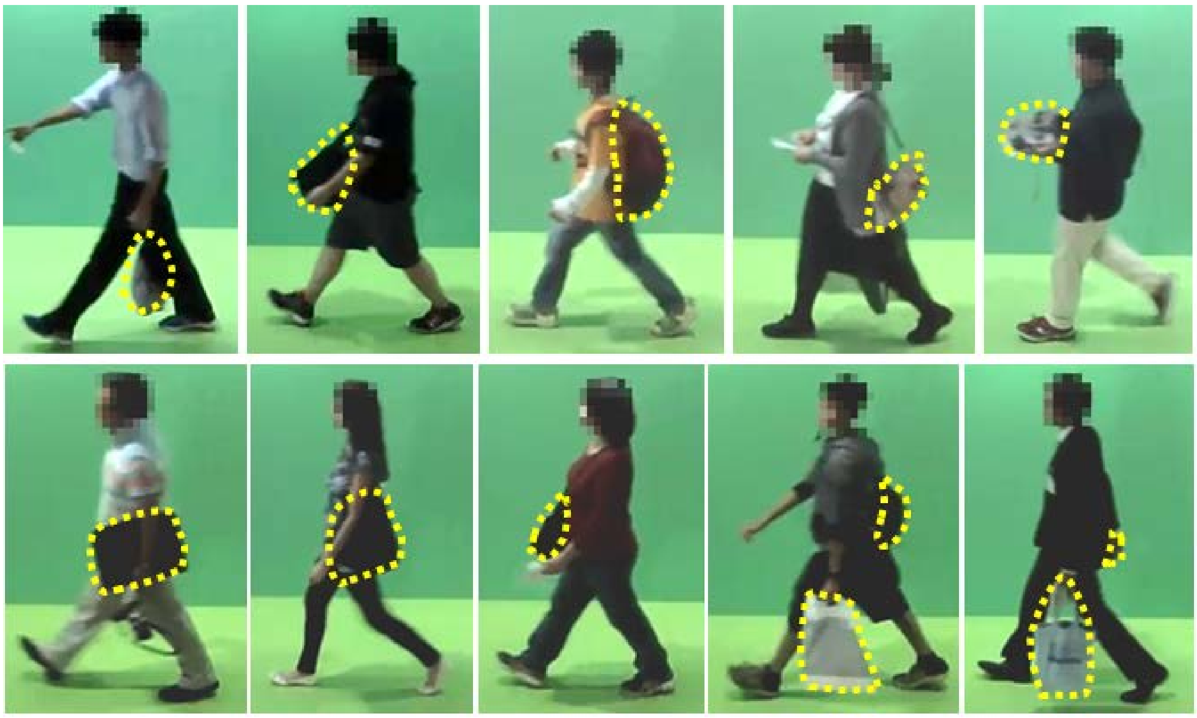


Figure 6-1: OU-ISIR carrying object examples

6.1 OU-ISIR Large Population dataset with Bag

It is the largest dataset that focuses on gait samples with various bag statuses. It has been published in 2017. In the β version, it has 2070 subjects of which each subject has two sample sequences, one with and one without a carrying object. The dataset is divided into two datasets, 1034 subjects in the training dataset and 1036 subjects in the testing dataset. Sequences without a carrying object are chosen as the gallery sample and the other sequences are used as a probe sample. There is no restriction for clothing so there are various appearances in the dataset.

In the β version, GEI representation is already provided and some samples are shown in Figure 6.2. Experiments conducted in this Chapter used these GEIs as the basic gait representation and extended it into three gait representations as described in Chapter 4. Training and testing dataset are completely divided or each subject only appears in one dataset. Each dataset has their own gallery and probe samples. Some technique such as metric learning [116] uses the training dataset for parameter learning. And the performance of them is tested by testing dataset. Because the proposed framework does not need parameters learning, both datasets can be directly tested under the proposed framework. In this research, each dataset in this Chapter is trained and tested separately.

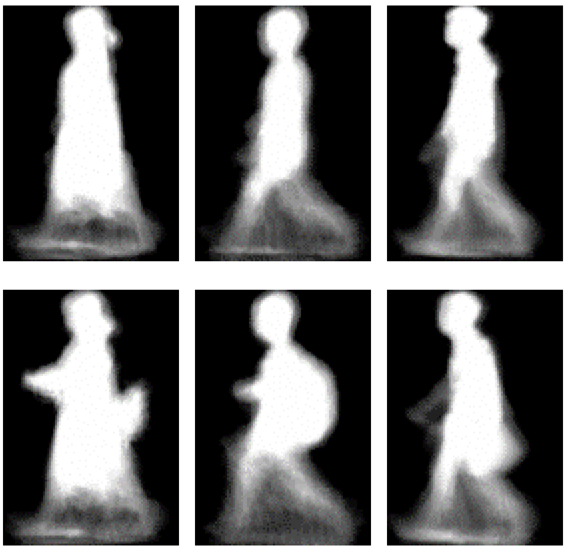


Figure 6-2: OU-ISIR Provided GEI samples

6.2 Gait Recognition by using body parts

This experiment focuses on the single body part which is from twelve different body parts as seen in Table 5.1 and Figure 5.2. Each part is trained and tested by four gait representations, GEI, CGI, GHGI and CGHGI.

6.2.1 Single Part (SP) Evaluation

Twelve different body parts had been separately trained and tested by PCA and SVM as shown in Figure 5.1. Testing and training dataset had a different number of subjects. Gait representation was applied with the optimal feature map calculated by PCA which reduced the dimension data size to 1024. Personal models were trained and tested by one reduced data of each person. Gallery samples which captured subjects without a carried object were used in training. Optimized feature map by PCA which was applied with gait representation to reduce data dimension was calculated from these samples. Probe samples which captured the subjects with a carried object were used in the testing phase.

Table 6-1: Cell size test

Dataset	Cell Size	Part												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
Training	1x1	53.00	11.03	18.09	25.92	22.05	24.56	30.46	19.73	42.94	41.97	26.50	27.37	28.63
	2x2	57.83	13.44	20.41	27.85	25.24	26.31	30.95	19.44	48.16	45.74	35.40	34.43	**32.10**
	3x3	56.19	12.96	20.21	27.85	24.08	24.47	28.72	16.92	46.32	47.00	36.94	35.98	31.47
	4x4	54.74	13.93	19.83	27.27	22.92	24.66	28.24	17.70	44.29	43.71	37.04	35.88	30.85
	5x5	52.03	12.67	19.44	28.24	21.37	22.34	25.82	15.38	39.94	41.97	35.88	35.30	29.20
Testing	1x1	52.22	9.85	19.40	26.83	23.36	23.84	27.61	20.17	39.58	38.90	25.39	27.41	27.88
	2x2	53.76	12.45	22.78	30.31	24.23	24.81	28.86	20.95	43.34	43.63	32.24	31.76	**30.76**
	3x3	52.70	11.68	22.01	29.15	24.61	23.75	27.03	18.92	42.76	43.44	34.85	33.59	30.37
	4x4	50.58	12.93	21.72	29.34	24.13	25.10	26.16	18.63	42.08	43.92	36.97	35.62	30.60
	5x5	48.65	11.00	20.46	30.69	23.07	22.97	24.13	16.89	39.96	41.70	35.04	35.14	29.14
Average	1x1	52.61	10.44	18.74	26.38	22.70	24.20	29.04	19.95	41.26	40.44	25.94	27.39	28.26
	2x2	55.80	12.95	21.59	29.08	24.73	25.56	29.90	20.19	45.75	44.69	33.82	33.09	**31.43**
	3x3	54.45	12.32	21.11	28.50	24.35	24.11	27.88	17.92	44.54	45.22	35.89	34.78	30.92
	4x4	52.66	13.43	20.77	28.31	23.53	24.88	27.20	18.16	43.19	43.82	37.00	35.75	30.72
	5x5	50.34	11.84	19.95	29.47	22.22	22.66	24.98	16.13	39.95	41.84	35.46	35.22	29.17

In this Chapter, HOG parameters were set up by the following steps. The first was cell size test which used block size 2x2 and 9 orientation histogram bins. All datasets had the best average classification rate when cell size was 2x2 as it can be seen in Table 6.1. The second was block size test which used cell size 2x2 and 9 orientation histogram bins. Training, testing and average dataset had different best-averaged block size as 3x3, 4x4 and 3x3, respectively, as presented in Table 6.2. The last was the orientation histogram bins test which used cell size 2x2 and block size 3x3. All datasets had the same best-averaged orientation histogram bins of 36 as it can be seen in Table 6.3. Nonetheless, 18 orientation histogram bins which reduced the output by half had slightly lower classification rate than 36 orientation histogram bins. Therefore this experiment used 18 orientation histogram bins for HOG to reduce the computational cost.

Table 6-2: Block size test

Set	**Block Size**	**Part**												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
Train	1x1	54.45	11.12	17.12	24.56	20.70	22.34	28.43	18.47	44.39	42.94	31.91	30.37	28.90
	2x2	57.83	13.44	20.41	27.85	25.24	26.31	30.95	19.44	48.16	45.74	35.40	34.43	32.10
	3x3	57.74	14.70	21.47	29.21	25.53	25.44	31.14	19.73	47.58	47.20	36.17	33.75	**32.47**
	4x4	57.93	15.57	20.89	28.14	24.27	25.05	31.43	19.92	46.62	46.52	35.98	34.62	32.25
	5x5	56.77	13.64	19.15	31.24	24.66	25.24	29.79	18.09	45.84	46.71	35.49	35.88	31.87
	6x6	56.09	12.86	20.31	27.37	22.53	23.69	28.72	16.92	46.03	46.52	35.88	35.59	31.04
Test	1x1	50.68	10.14	17.47	26.54	21.62	22.20	26.64	18.24	40.15	39.96	28.76	29.83	27.69
	2x2	53.76	12.45	22.78	30.31	24.23	24.81	28.86	20.95	43.34	43.63	32.24	31.76	30.76
	3x3	53.28	13.03	23.94	30.60	25.19	25.48	28.96	20.85	44.40	44.02	33.40	32.82	31.33
	4x4	53.86	13.71	23.65	29.63	25.29	25.97	29.44	21.04	44.40	43.82	33.98	33.49	**31.52**
	5x5	52.41	12.07	22.97	31.18	25.29	25.77	28.76	19.21	44.88	45.37	34.17	33.59	31.31
	6x6	51.83	9.85	22.68	27.61	25.39	25.29	27.51	18.05	44.02	43.34	35.81	34.85	30.52
Average	1x1	52.56	10.63	17.29	25.55	21.16	22.27	27.54	18.36	42.27	41.45	30.34	30.10	28.29
	2x2	55.80	12.95	21.59	29.08	24.73	25.56	29.90	20.19	45.75	44.69	33.82	33.09	31.43
	3x3	55.51	13.87	22.70	29.90	25.36	25.46	30.05	20.29	45.99	45.61	34.78	33.29	**31.90**
	4x4	55.90	14.64	22.27	28.89	24.78	25.51	30.44	20.48	45.51	45.17	34.98	34.06	31.88
	5x5	54.59	12.85	21.06	31.21	24.98	25.51	29.28	18.65	45.36	46.04	34.83	34.74	31.59
	6x6	53.96	11.35	21.50	27.49	23.96	24.49	28.12	17.49	45.03	44.93	35.85	35.22	30.78

This experiment set HOG and convolutional parameters as follows. CGI used filter size 3x3x1x16 for the convolutional method. GHGI used cell size 2x2, block size 3x3 and 18 orientation histogram bins for HOG. CGHGI used the same parameters as GHGI for HOG and filter size 3x3x18x36 for the convolutional method. Results which are separated by datasets and gait representations were demonstrated in Table 6.4.

Table 6-3: Orientation histogram bins test

Set	Bins	Part												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
Train	9	57.74	15.67	21.47	29.98	25.53	25.44	31.14	19.83	47.87	47.20	36.17	33.75	32.65
	10	58.03	15.86	21.18	30.95	26.21	26.02	31.62	20.41	48.26	47.49	35.78	34.24	33.00
	12	59.38	16.15	22.63	32.11	27.08	28.24	32.88	22.05	49.81	48.94	36.17	35.20	34.22
	15	59.96	16.83	22.53	33.08	28.43	29.50	34.43	23.02	51.06	49.61	36.07	36.85	35.11
	18	61.51	17.41	22.53	33.85	28.53	30.56	35.30	23.69	51.55	49.90	36.36	36.65	35.65
	20	61.99	17.02	23.21	33.56	28.92	30.95	35.11	24.08	51.35	50.29	37.23	37.43	35.93
	30	61.70	16.44	23.31	34.72	29.50	31.24	35.98	25.63	52.13	50.77	36.36	36.75	36.21
	36	61.99	16.92	23.79	34.91	29.79	31.04	35.98	26.50	52.71	51.06	36.17	36.94	**36.48**
Test	9	53.28	13.51	23.94	31.47	25.19	25.48	28.96	21.33	44.79	44.02	33.40	32.82	31.52
	10	55.12	13.71	24.32	32.53	26.35	26.64	29.73	21.53	45.37	45.08	33.88	33.49	32.31
	12	56.76	14.67	24.61	33.49	27.22	27.41	30.79	22.39	46.43	46.24	34.75	34.46	33.27
	15	57.72	14.96	25.97	33.88	28.76	27.99	32.72	23.17	47.97	47.39	35.14	34.75	34.20
	18	58.59	14.96	26.74	34.27	28.96	29.15	33.59	24.42	48.75	47.68	35.62	35.04	34.81
	20	58.88	15.44	26.45	34.46	29.54	29.63	33.49	24.81	48.84	48.84	35.42	35.14	35.08
	30	59.27	15.64	26.54	35.04	29.73	30.41	34.94	26.93	49.81	48.46	35.52	35.04	35.61
	36	59.27	14.86	26.25	35.14	30.31	31.18	35.14	27.03	49.32	49.03	35.71	34.94	**35.68**
Average	9	55.51	14.59	22.70	30.72	25.36	25.46	30.05	20.58	46.33	45.61	34.78	33.29	32.08
	10	56.57	14.78	22.75	31.74	26.28	26.33	30.68	20.97	46.81	46.28	34.83	33.87	32.66
	12	58.07	15.41	23.62	32.80	27.15	27.83	31.84	22.22	48.12	47.59	35.46	34.83	33.74
	15	58.84	15.89	24.25	33.48	28.60	28.74	33.58	23.09	49.52	48.50	35.60	35.80	34.66
	18	60.05	16.18	24.64	34.06	28.74	29.86	34.45	24.06	50.15	48.79	35.99	35.85	35.23
	20	60.44	16.23	24.83	34.01	29.23	30.29	34.30	24.44	50.10	49.57	36.33	36.28	35.50
	30	60.48	16.04	24.93	34.88	29.61	30.82	35.46	26.28	50.97	49.61	35.94	35.89	35.91
	36	60.63	15.89	25.02	35.02	30.05	31.11	35.56	26.76	51.02	50.05	35.94	35.94	**36.08**

Table 6-4: Single part gait recognition under OU-ISIR dataset

Part	GEI		CGI		GHGI		CGHGI	
	training	testing	training	testing	training	testing	training	testing
1	32.11	31.18	33.43	31.66	61.51	58.59	60.54	58.27
2	9.19	9.17	8.22	7.30	17.41	14.96	16.70	15.06
3	15.28	14.77	13.09	12.64	22.53	26.74	21.66	25.61
4	21.76	21.81	19.66	19.40	33.85	34.27	32.56	33.91
5	14.70	17.37	14.73	16.15	28.53	28.96	27.63	28.44
6	16.15	17.28	14.96	16.70	30.56	29.15	28.76	28.47
7	17.99	18.73	16.47	19.66	35.30	33.59	34.43	33.20
8	12.86	13.61	12.48	13.19	23.69	24.42	23.37	23.33
9	27.56	24.61	24.56	24.45	51.55	48.75	50.87	48.36
10	29.59	27.80	25.24	24.97	49.90	47.68	49.45	47.36
11	29.11	28.09	20.02	20.66	36.36	35.62	35.72	34.17
12	31.33	31.08	24.37	25.16	36.65	35.04	34.43	34.20

In Table 6.4, part 1 or full body had the best classification rate of which GHGI had the highest classification rate at 61.51% training dataset and 58.59% testing dataset. Part 12 ranked in the second in case of GEI and CGI while part 9 took the second rank in case of GHGI and CGHGI. Overall, GHGI had the highest classification rate followed by CGHGI, GEI and CGI in order.

6.2.2 Discussion

In the OU-ISIR large population dataset with bag, each person has two image sequences, one with a carried object and the other without a carried object. The style, position and size of these objects vary as it can be seen in Figure 6.1. Moreover, people involved dressed without restriction which may obstruct or obscure some body part movement. All these reasons may cause the low classification rate with GEI to which all images from complete gait cycle sequence are simply averaged into one compact image. CGI which is derived from GEI by convolutional techniques had a similar result with GEI. Although CGI had lower classification rate than GEI in most cases CGI full body did have slightly higher classification rate than GEI. The five top classification rates for GEI were 31.64% part 1, 31.21% part 12, 28.70% part 10, 28.60% part 11 and 26.09% part 9 as they had been shown in Table 6.2. For CGI, the top five classification rates were 32.55% part 1, 25.10% part 10, 24.77% part 12, 24.51% part 9 and 20.34% part 11, as shown in Table 6.5.

Table 6-5: Single part averaged classification rate

Part	GEI	CGI	GHGI	CGHGI
1	**31.64**	**32.55**	**60.05**	**59.41**
2	9.18	7.76	16.18	15.88
3	15.02	12.87	24.64	23.64
4	21.79	19.53	34.06	33.24
5	16.04	15.44	28.74	28.04
6	16.71	15.83	29.86	28.62
7	18.36	18.07	34.45	33.82
8	13.24	12.83	24.06	23.35
9	**26.09**	**24.51**	**50.15**	**49.61**
10	**28.70**	**25.10**	**48.79**	**48.41**
11	**28.60**	**20.34**	**35.99**	**34.94**
12	**31.21**	**24.77**	**35.85**	**34.32**

The HOG technique has enormously improved the classification rate as shown in Tables 6.4 and 6.5. GHGI and CGHGI had better classification rate than GEI and CGI. The best five-recognition rates associated with parts for GHGI were 60.05% part 1, 50.15% part 9, 48.79 % part 10, 35.99% part 11 and 35.85% part 12, whilst the top five classification rates associated with parts for CGHGI were 59.41% part 1, 49.61% part 9, 48.41% part 10, 34.94% part 11 and 34.32% part 12.

All representations had the best classification rate with lower body parts. These show the potential contribution of lower body parts, such as a limb, lower hip, lower knee and ankle region to gait recognition with respect to the dataset.

6.3 Partial Body Fusion Gait Recognition

This section investigates gait recognition by two selected body parts fusion in three different approaches, part score fusion, part image fusion and multi region duplication. All approaches are the same as in Chapter 5, nonetheless, the main dataset in this Chapter is changed to OU-ISIR large population dataset with bag β version. Another different point is the selected parts. In Chapter 5, seven body parts having average classification rates over 80% are chosen for all gait representations. In this Chapter, only six body parts are used. They are parts 1, 4, 9, 10, 11 and 12 from which a relatively higher averaged classification rate are achieved from all gait representations as they are shown in Table6.5. The fusion of selected parts is shown in Table 6.6.

Table 6-6: Part fusion for Chapter 6 experiment

fusion	part 1	part 2
1	1	2
2	1	9
3	1	10
4	1	11
5	1	12
6	2	9
7	2	10
8	2	11
9	2	12

6.3.1 Part Score Fusion (PSF) Evaluation

For the part score fusion approach, two personal models for each subject were trained separately by two selected parts in the training phase. In the testing phase, each personal model was tested by the same part from the probe sample. The final score to an individual was an average from both personal models. The highest personal score was chosen as the prediction result. The results of the classification rate are shown in Table 6.7.

Table 6-7: Part score fusion results

fusion	GEI		CGI		GHGI		CGHGI	
	training	testing	training	testing	training	testing	training	testing
1	34.82	33.20	32.50	30.56	56.29	55.50	56.44	48.61
2	34.24	31.08	32.86	31.81	63.15	61.97	63.83	49.32
3	35.69	32.82	34.29	32.92	64.12	62.16	64.22	49.92
4	39.46	34.75	36.91	33.20	62.86	59.85	62.48	48.12
5	40.52	35.14	37.18	34.88	62.57	60.14	62.01	48.07
6	35.78	34.46	33.68	32.37	58.99	57.53	58.82	46.85
7	36.27	36.20	35.30	32.64	58.80	57.05	58.43	45.59
8	38.68	38.80	33.69	28.63	52.32	50.48	51.88	38.34
9	40.91	39.48	35.30	30.54	52.71	50.68	52.01	37.14

From Table 6.7, it can be seen that the best classification rate was 64.22% CGHGI at fusion 3 for the training dataset and 62.16% GHGI at fusion 3 for the testing dataset. If only training dataset had been considered, the best classification rate for each gait representation was 40.91% GEI fusion 9, 37.18% CGI at fusion 5, 64.12% GHGI at fusion 3 and 64.22% CGHGI at fusion 3. On the other hand, the best classification rates for the testing dataset were 39.48% GEI at fusion 9, 34.88% CGI at fusion 5, 62.16% GHGI at fusion 3 and 49.92% CGHGI at fusion 3.

There were many fusions which had higher classification rates than the best single part or full body. All GEI fusions except for fusion 2 with the testing dataset had higher classification rate than GEI single part. Only CGI at fusion 1 with both dataset and 2 training dataset had a lower classification rate than the best CGI single part, while the rest had a higher classification rate. GHGI fusions 2 to 5 had higher classification rates than the best GHGI single part. Lastly, CGHGI at fusions 2 to 5 had higher classification rate than the best CGHGI single part for the training dataset while all CGHGI fusions for the testing dataset had lower classification rates than the best CGHGI single part. Nevertheless, almost all fusions 6 to 9 in which part 1 was not involved, had higher classification rate than their best-selected single parts, except CGHGI at fusion 6 and 7 for the testing dataset had lower classification rate than single parts 9 and 10.

6.3.2 Part Image Fusion (PIF) Evaluation

The part image fusion concatenates both selected parts into a single image before the recognition processes as shown in Figure 5.4. The image fusion was used as input for the general gait recognition system as shown in Figure 5.1. Chapter 5 and this experiment used the same gait recognition framework, nonetheless, in Chapter 5, a personal model was trained in one view angle per person each time. If four normal walk datasets had been used in the training phase, the maximum gait representations which must be loaded into the memory at the same time contains 116x4 or 496 images. However, this Chapter must load 1034 gait representations when uses a training dataset or 1036 gait representations when uses a testing dataset. PIF and MRD input images which concatenated two selected parts together are larger than the normal full body image. In addition, HOG and convolutional techniques also enlarged gait representation size. Both reasons made GHGI and CGHGI experiments used more run-time memory or RAM for PIF and MRD.

Table 6-8: Gait representation size

Parameter setting			
Cell size	2x2	2x2	3x3
Block size	3x3	4x4	2x2
Bins	18	18	18
Filter	3x3x18x36	3x3x18x36	3x3x18x36
Gait representation size			
GHGI part 1	421,848 (186x126x18)	187,488 (124x84x18)	82,656 (82x56x18)
CGHGI part 1	821,374 (184x124x36)	360,144 (122x82x36)	155,520 (80x54x36)
PIF GHGI fusion 2	625,968 (276x126x18)	278,208 (184x84x18)	122,976 (122x56x18)
PIF CGHGI fusion 2	1,223,136 (274x124x36)	537,264 (182x82x36)	233,280 (120x54x36)
MRD GHGI fusion 2 (1:2)	830,088 (366x126x18)	368,928 (244x84x18)	163,296 (162x56x18)
MRD GHGI fusion 2 (1:3)	1,034,208 (456x126x18)	459,648 (304x84x18)	203,616 (202x56x18)
MRD GHGI fusion 2 (1:4)	1,238,328 (546x126x18)	550,368 (364x84x18)	243,936 (242x56x18)
MRD CGHGI fusion 2 (1:2)	1,624,896 (364x124x36)	714,384 (242x82x36)	311,040 (160x54x36)
MRD CGHGI fusion 2 (1:3)	2,026,656 (454x126x36)	891,504 (302x82x36)	388,800 (200x54x36)
MRD CGHGI fusion 2 (1:4)	2,428,416 (544x124x36)	1,068,624 (362x82x36)	466,560 (240x54x36)

Original GEI size was 128x88=11,264 pixels. If part 1 was excluded, part 9 has the largest size of 60x88=5,280. The largest fusion was fusion 2 (188x88 or 16,544) which fused part 1 (128x88) and 9 (60x88). The optimized HOG parameters were of cell size 2x2, block size 3x3 and 36 orientation histogram bins. Both HOG and convolutional techniques enormously increased the output gait representation size when compared with original GEI as it can be seen in Table 6.8. For instance, the optimized parameter made the PIF CGHGI fusion 2 have a size of 1,223,136. If all values are stored with a double type variable, it needs 9,785,088 or 9.79 MB memory per gait representation. All representations can be stored in RAM. Nonetheless, the run-time memory during PCA process is depended on the size of each representation. The system may crash during PCA process if it did not have enough memory. This problem could be solved by changing the parameters.

This experiment set HOG parameters as cell size 2x2, block size 4x4 which had the second highest classification rate in Table 6.2. The classification rate is shown in Table 6.9. The best classification rate was 63.77% CGHGI at fusion 3 for the training dataset and 62.84% GHGI at fusion 3 for the testing dataset. If only training dataset had been considered, the best classification rate for the gait representation was 39.07% GEI at fusion 9, 33.83% CGI at fusion 7, 63.73% GHGI at fusion 3 and 63.77% GHGI at fusion 3. In contrast, the best classification rate for the testing dataset was 39.58% GEI at fusion 9, 33.15 CGI at fusion 7, 62.84% GHGI at fusion 3 and 62.26% CGHGI at fusions 3 and 6.

Table 6-9: Part image fusion results

fusion	GEI		CGI		GHGI		CGHGI	
	training	testing	training	testing	training	testing	training	testing
1	32.69	32.05	31.16	29.38	62.48	58.69	61.44	58.75
2	33.17	30.60	31.22	29.32	62.19	61.97	62.41	61.52
3	33.85	31.08	31.76	29.98	63.73	62.84	63.77	62.26
4	34.24	32.05	32.73	30.29	63.93	61.20	63.28	61.13
5	33.95	32.34	32.77	30.37	63.54	61.97	63.41	61.26
6	36.65	35.62	32.77	32.07	62.38	62.26	62.89	62.26
7	38.01	37.16	33.83	33.15	62.48	62.45	62.54	61.87
8	38.59	39.09	32.03	32.22	57.64	55.60	56.38	54.60
9	39.07	39.58	32.34	32.26	56.00	55.60	56.45	55.44

Almost all of the fusions had better classification rate than the best single part for GEI, GHGI and CGHGI while almost all fusions had worse classification rate than single part 1 for CGI. Only GEI fusions 2 and 3 had a lower classification rate than single part 1 for the testing dataset. Only CGI at fusion 7 for the training dataset and at fusions 6 to 9 for the testing dataset had higher classification rates than single part 1. Both GHGI and CGHGI at fusions 8 and 9 had lower classification rates than full body in both the training and testing datasets. Nonetheless, all fusions from 6 to 9 had better classification rates than a single selected part for all gait representations and datasets.

6.3.3 Multi Region Duplication (MRD) Evaluation

This part fusion approach concatenated selected parts with a different ratio. Selected parts for each fusion are shown in Table 6.6. As it can be seen in Table 6.8, MRD had the best classification rate with parameters which were of cell size 2x2, block size 3x3 and 18 orientation histogram bins. The resulted representation was very large especially for CGHGI at fusion 2 (1:4) as it can be seen in Table 6.8. Although HOG parameters were reduced to cell size 2x2, block size 4x4 and 18 orientation histogram bins as the same with PIF experiment, CGHGI at fusion 2 (1:4) still had larger than 1 million values. This experiment decided to use cell size 3x3 and block size 2x2 with which the second highest classification rate was achieved as shown in Table 6.1. As it can be seen in Table 4.11, with such HOG parameters the gait representation size would be smaller than that from cell size 2x2 and block size 5x5 which produced the third highest classification rate in Table 6.2. Convolutional filter size was 3x3x18x36. Results are shown in Table 6.10.

The best classification rate for MRD ratio 1:2 was 62.38% GHGI at fusion 3 for the training dataset and 61.29% GHGI at fusion 5 for the testing dataset. If the classification rate results were compared with the best single part or full body in Table 6.5, almost all fusions results have a higher classification rate. These included all GEI fusions except that of fusion 2 testing dataset, all CGI fusions except for fusion 2, GHGI fusion 3, 6 and 7 - training dataset, GHGI fusions 2 to 7 - testing dataset, CGHGI fusions 3 to 7 – training dataset and CGHGI fusions 1 and 3 to 7.

Table 6-10: Multi Region Duplicate results

Ratio	Representation	dataset	Fusion 1	2	3	4	5	6	7	8	9
1:2	GEI	train	34.24	32.59	34.24	35.69	35.88	35.20	38.20	39.17	40.14
		test	32.24	30.12	31.37	32.34	32.92	34.36	36.29	39.48	40.44
	CGI	train	35.07	32.91	33.46	35.69	37.27	33.56	35.27	36.01	39.20
		test	33.66	30.86	31.98	33.11	34.52	33.56	35.78	35.26	38.29
	GHGI	train	59.28	60.83	62.38	61.41	61.32	62.09	61.99	54.84	56.29
		test	58.20	59.36	60.62	61.00	61.29	61.00	60.42	54.25	54.54
	CGHGI	train	59.99	59.96	60.74	61.99	62.19	60.90	60.61	56.51	57.32
		test	58.49	58.24	59.20	60.75	61.13	59.30	59.62	54.60	55.31
1:3	GEI	train	33.95	32.79	34.04	35.40	36.27	34.43	37.52	40.14	41.78
		test	32.82	30.21	31.66	33.01	33.78	33.20	35.91	39.38	41.31
	CGI	train	33.66	32.69	33.56	35.78	36.36	33.46	37.33	40.14	41.78
		test	32.24	30.69	31.47	32.82	33.69	34.36	35.62	38.42	40.64
	GHGI	train	57.45	59.48	60.74	59.28	60.25	59.96	60.15	52.61	54.64
		test	56.56	58.40	59.94	58.88	60.42	59.75	59.36	51.64	53.09
	CGHGI	train	58.83	58.51	59.77	60.96	62.09	59.38	58.87	54.67	54.58
		test	57.27	57.14	58.66	60.17	60.75	58.04	58.43	52.99	54.09
1:4	GEI	train	34.43	32.30	33.85	35.88	36.85	33.37	37.04	40.52	42.84
		test	33.01	29.54	31.18	33.30	34.17	32.53	35.62	38.80	41.41
	CGI	train	33.56	29.69	31.04	34.33	37.91	30.37	30.66	31.72	37.23
		test	33.59	27.90	28.76	31.47	36.78	28.67	30.69	30.41	36.39
	GHGI	train	55.03	58.32	58.70	57.64	58.61	58.22	58.41	50.00	52.61
		test	55.31	56.95	58.11	57.43	58.78	58.69	58.88	49.61	51.74
	CGHGI	train	55.80	57.09	58.51	59.57	60.77	57.41	57.22	52.19	52.97
		test	55.60	56.18	55.50	57.56	58.72	55.79	55.79	51.06	51.42

The best classification rate for MRD ratio 1:3 was 62.09% CGHGI at fusion 5-training dataset and 60.75% CGHGI at fusion 5-testing dataset. The list of fusions which had better classification rates than single part 1 included all GEI fusions except that of fusion 2 – testing dataset, all CGI fusions except for fusion 2 - both datasets and 3 - testing dataset, GHGI fusions 3 to 7 – testing dataset, CGHGI fusions 4 to 5 – training dataset and fusions 3 to 5 and 7 – testing dataset.

The best classification rate for MRD ratio 1:4 was 60.77% CGHGI at fusion 5-training dataset and 58.88% CGHGI at fusion 7-testing dataset. Almost all fusions had lower classification rates than single part 1 except of all GEI fusions – training dataset, GEI fusions 1, 4 to 9 – testing dataset, CGI fusions 1, 4, 5 and 9 – training dataset and fusions 1, 5 and 9 – testing dataset, GHGI fusions 5 to 7 – testing dataset and CGHGI fusion 5 – both datasets.

Almost all gait representations had the same classification rate trend. When the number of second part ratio increased, the classification rate decreased. Only GEI fusion 8 and 9 had explicitly broken this trend especially fusion 9 (1:4) had a classification rate that is 10% higher than that of single part 1.

6.3.4 Discussion

The part fusion which uses two selected parts instead of the single part has a higher classification rate than the best single part. Nonetheless, the part fusion approach and selected part must be carefully chosen. There are three part fusion approaches in this study including part score fusion (PSF), part image fusion (PIF) and multi-region duplication (MRD). Each approach has nine fusions, as shown in Table 6.5. The best classification rate for each fusion part approach was 64.22% CGHGI at fusion 3 for the training dataset and 62.16 GHGI at fusion 3 for the testing dataset. If only the training dataset had been considered, the best classification rate for each gait representation was 42.84% GEI MRD at fusion 9 (1:4), 40.14% CGI MRD at fusion 9 (1:3), 64.12% GHGI PSF at fusion 3 and 64.22% CGHGI PSF at fusion 3. In case of the testing dataset, the best recognition for each representation was 41.41% GEI MRD at fusion 9 (1:4), 40.64% CGI MRD at fusion 9 (1:3), 62.16% GHGI PSF at fusion 3 and 62.26% CGHGI PIF at fusions 3 and 6.

If both the training and testing datasets had been considered, the average classification rate is shown in Figure 6.3. This average value was the mean between both the datasets which were separately trained and tested in this section. As it can be seen, HOG gait representation had higher classification rate than GEI and CGI.

GEI PSF worked better than the other part fusion approaches when part 1 was chosen as one selected part. The best fusion 5 had a classification rate of 37.83% followed by fusion 4 of 37.10%. When part 1 did not involve or some body parts were excluded, the image fusion had a better classification rate than score fusion. Especially, fusions 8 and 9 which fused part 4 with part 11 and 12 had better classification rate when the number of duplicate parts increased. This showed the potential of parts 11 and 12 in gait recognition.

Figure 6-3: Averaged classification rate of part fusion gait representation

For CGI, PSF worked better than PIF whilst PSF worked well with fusions when part 1 is involved. MRD 1:2 and 1:3 had a better classification rate than PSF and MRD 1:4 except at fusions 1 and 5. MRD 1:2 had better classification rate than MRD 1:3 when part 1 had been used as a selected part. In another way, MRD 1:3 worked better than MRD 1:2 when part 1 was not one of the selected parts. If the lower body parts had been considered, the classification rate was increased when the size of the second part was decreased as it could be seen from fusions 2 to 5 and fusions 6 to 9. Especially, fusion 5 MRD 1:4 and 9 MRD 1:3 in which one selected part, was part 11, had the best results. This pattern was the same as for the GEI representation.

In contrast, GHGI and CGHGI worked well with the PIF approach which fused two selected parts with ratio 1:1 into a single image. If the lower body parts were considered, the classification rate usually decreased when part size decreased as it can be seen in fusions 2 to 5 and fusions 6 to 9. Only CGI at fusions 8 and 9 MRD 1:2 had slightly higher classification rate than PIF. GHGI and CGHGI didn't show good result at fusions 8 and 9 which had parts 10 and 11 as a selected part. The best classification rate of fusions 2 to 6 was very similar. This means fusions 5 and 6 which had some missing body parts had potential in gait recognition. Alternatively, the mid body parts could be ignored in gait recognition.

6.4 Summary

The OU-ISIR Large population dataset with the bag is currently the largest dataset which captures two sequences of walking videos per person. One is normal walking without bag and the other is walking with bag. Their outfit and bag are both in freestyle because they use their own clothing and bag. Additionally, they also carried their bag with their own styles. This β version dataset is divided into two datasets which include 1034 subjects in the training dataset and 1036 subjects in the testing dataset.

Table 6-11: Summarized of single part gait recognition

Representation	Set	Part											
		1	2	3	4	5	6	7	8	9	10	11	12
GEI	training	**32.11**	9.19	15.28	**21.76**	14.7	16.15	17.99	12.86	**27.56**	**29.59**	**29.11**	**31.33**
	testing	**31.18**	9.17	14.77	**21.81**	17.37	17.28	18.73	13.61	**24.61**	**27.8**	**28.09**	**31.08**
	Mean	**31.64**	9.18	15.02	**21.79**	16.04	16.71	18.36	13.24	**26.09**	**28.7**	**28.6**	**31.21**
CGI	training	**33.43**	8.22	13.09	**19.66**	14.73	14.96	16.47	12.48	**24.56**	**25.24**	**20.02**	**24.37**
	testing	**31.66**	7.3	12.64	**19.4**	16.15	16.7	19.66	13.19	**24.45**	**24.97**	**20.66**	**25.16**
	Mean	**32.55**	7.76	12.87	**19.53**	15.44	15.83	18.07	12.83	**24.51**	**25.1**	**20.34**	**24.77**
GHGI	training	**61.51**	17.41	22.53	33.85	28.53	30.56	**35.3**	23.69	**51.55**	**49.9**	**36.36**	**36.65**
	testing	**58.59**	14.96	26.74	**34.27**	28.96	**29.15**	33.59	24.42	**48.75**	**47.68**	**35.62**	**35.04**
	Mean	**60.05**	16.18	24.64	34.06	28.74	29.86	**34.45**	24.06	**50.15**	**48.79**	**35.99**	**35.85**
CGHGI	training	**60.54**	16.7	21.66	32.56	27.63	28.76	**34.43**	23.37	**50.87**	**49.45**	**35.72**	**34.43**
	testing	**58.27**	15.06	25.61	**33.91**	28.44	28.47	33.2	23.33	**48.36**	**47.36**	**34.17**	**34.2**
	Mean	**59.41**	15.88	23.64	33.24	28.04	28.62	**33.82**	23.35	**49.61**	**48.41**	**34.94**	**34.32**
Average		**45.91**	12.25	19.04	**27.15**	22.06	22.75	26.17	18.37	**37.59**	**37.75**	**29.97**	**31.53**

The summarized result of single part gait recognition experiments is shown in Table 6.11. GHGI and CGHGI which use HOG technique have better classification rate than GEI and CGI. Full body or part 1 has the best classification rate following by the lower body parts, such as parts 9, 10, 11 and 12. The sixth best part is parts 4 and 7 depending on gait representation and dataset. Nonetheless, part 4 is chosen for part fusion experiments because part 4 has a better average classification rate than part 7.

The summarized result of part fusion gait recognition is shown in Table 6.12. All highlighted results have lower classification rate than that of single part 1 which is the best part from single part experiments. If each gait representation is separately considered, GEI fusion except that of fusions 2 and 3 for the testing dataset always has better classification rate than full body. Especially GEI at fusions 8 and 9 MRD 1:4 has a classification rate of approximately 10% better than part 1 alone does. GEI PSF has a better classification rate than the other fusion approaches when part 1 is chosen as a selected part.

CGI MRD 1:2 and 1:3 usually have better classification rate than the other approaches especially MRD 1:2 at fusion 9 and MRD 1:3 at fusions 8 and 9. When parts 11 and 12 are involved in a selected part, the classification rate is higher than the other fusions.

GHGI and CGHGI PSF-PIF have a slightly better result than the other approaches. If the image fusion is considered, the classification rate is decreased when the size of the second part is decreased. GHGI and CGHGI fusions 8 and 9 at which GEI and CGI representations have better classification rate have worse classification rate than the other fusions.

Finally, if part 1 or full body is excluded or there are some missing body parts, fusions 6 to 9 always give better classification rate than the other two selected parts in each fusion. Some fusions have better classification rate than the full body which has the best classification rate in the single part experiment. For example, all GEI at fusions 6 to 9, CGI MRD 1:2 and MRD 1:3 at fusions 6 to 9, GHGI and CGHGI PIF and MRD 1:2 at fusions 5 and 6.

Table 6-12: Part fusion summarized

Set	Approach	Representation	Fusion 1	2	3	4	5	6	7	8	9
Training	GEI	PSF	34.82	34.24	35.69	39.46	40.52	35.78	36.27	38.68	40.91
		PIF	32.69	33.17	33.85	34.24	33.95	36.65	38.01	38.59	39.07
		MRD 1:2	34.24	32.59	34.24	35.69	35.88	35.20	38.20	39.17	40.14
		MRD 1:3	33.95	32.79	34.04	35.40	36.27	34.43	37.52	40.14	41.78
		MRD 1:4	34.43	32.30	33.85	35.88	36.85	33.37	37.04	40.52	42.84
	CGI	PSF	32.50	32.86	34.29	36.91	37.18	33.68	35.30	33.69	35.30
		PIF	31.16	31.22	31.76	32.73	32.77	32.77	33.83	32.03	32.34
		MRD 1:2	35.07	32.91	33.46	35.69	37.27	33.56	35.27	36.01	39.20
		MRD 1:3	33.66	32.69	33.56	35.78	36.36	33.46	37.33	40.14	41.78
		MRD 1:4	33.56	29.69	31.04	34.33	37.91	30.37	30.66	31.72	37.23
	GHGI	PSF	56.29	63.15	64.12	62.86	62.57	58.99	58.80	52.32	52.71
		PIF	62.48	62.19	63.73	63.93	63.54	62.38	62.48	57.64	56.00
		MRD 1:2	59.28	60.83	62.38	61.41	61.32	62.09	61.99	54.84	56.29
		MRD 1:3	57.45	59.48	60.74	59.28	60.25	59.96	60.15	52.61	54.64
		MRD 1:4	55.03	58.32	58.70	57.64	58.61	58.22	58.41	50.00	52.61
	CGHGI	PSF	56.54	62.22	63.06	61.28	60.54	59.09	59.16	51.81	52.22
		PIF	61.44	62.41	63.77	63.28	63.41	62.89	62.54	56.38	56.45
		MRD 1:2	59.99	59.96	60.74	61.99	62.19	60.90	60.61	56.51	57.32
		MRD 1:3	58.83	58.51	59.77	60.96	62.09	59.38	58.87	54.67	54.58
		MRD 1:4	55.80	57.09	58.51	59.57	60.77	57.41	57.22	52.19	52.97
Testing	GEI	PSF	33.20	31.08	32.82	34.75	35.14	34.46	36.20	38.80	39.48
		PIF	32.05	30.60	31.08	32.05	32.34	35.62	37.16	39.09	39.58
		MRD 1:2	32.24	30.12	31.37	32.34	32.92	34.36	36.29	39.48	40.44
		MRD 1:3	32.82	30.21	31.66	33.01	33.78	33.20	35.91	39.38	41.31
		MRD 1:4	33.01	29.54	31.18	33.30	34.17	32.53	35.62	38.80	41.41
	CGI	PSF	30.56	31.81	32.92	33.20	34.88	32.37	32.64	28.63	30.54
		PIF	29.38	29.32	29.98	30.29	30.37	32.07	33.15	32.22	32.26
		MRD 1:2	33.66	30.86	31.98	33.11	34.52	33.56	35.78	35.26	38.29
		MRD 1:3	32.24	30.69	31.47	32.82	33.69	34.36	35.62	38.42	40.64
		MRD 1:4	33.59	27.90	28.76	31.47	36.78	28.67	30.69	30.41	36.39
	GHGI	PSF	55.5	61.97	62.16	59.85	60.14	57.53	57.05	50.48	50.68
		PIF	58.69	61.97	62.84	61.20	61.97	62.26	62.45	55.60	55.60
		MRD 1:2	58.20	59.36	60.62	61.00	61.29	61.00	60.42	54.25	54.54
		MRD 1:3	56.56	58.40	59.94	58.88	60.42	59.75	59.36	51.64	53.09
		MRD 1:4	55.31	56.95	58.11	57.43	58.78	58.69	58.88	49.61	51.74
	CGHGI	PSF	55.86	59.59	60.62	59.04	59.43	57.53	57.50	51.16	50.32
		PIF	58.75	61.52	62.26	61.13	61.26	62.26	61.87	54.60	55.44
		MRD 1:2	58.49	58.24	59.20	60.75	61.13	59.30	59.62	54.60	55.31
		MRD 1:3	57.27	57.14	58.66	60.17	60.75	58.04	58.43	52.99	54.09
		MRD 1:4	55.60	56.18	55.50	57.56	58.72	55.79	55.79	51.06	51.42

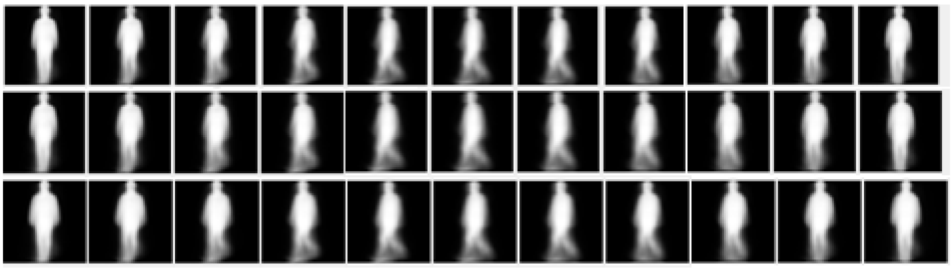
The comparison between this study and the other publication under the testing dataset are shown in Table 6.13. GHGI PIF fusion 3 (full body and lower hip) has the highest CCR.

Table 6-13: OU-LP-Bag β CCR comparison

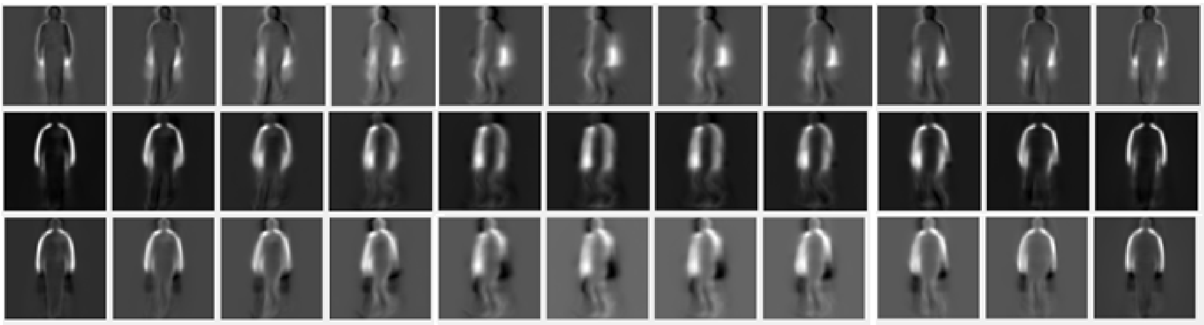
Method	**CCR**
GEI w/o LDA[116]	54.60
JI-ML w/ Ranking SVM[116]	57.40
GHGI	58.59
GEI MRD fusion 9	41.41
CGI MRD fusion 9	40.64
GHGI PIF fusion 3	**62.84**
CGHGI PIF fusion 3	62.26

Chapter 7 Conclusion and Future work

Gait, which is a physical and behavioural activity, is one of the most popular biometric subjects in this decade. Many research publications have shown that gait has a high potential for person identification applications. However, there are various factors that affect the gait recognition performance. This study focuses on gait recognition framework and gait representations with regards to the view angle and appearance changes covariance.



(a) Average all dataset GEI (1st row-normal walking, 2nd row-carrying a bag, 3rd row-wearing a coat)



(b) The difference between each appearance (1st row- normal walking and carrying a bag, 2nd row-normal waking and wearing a coat, 3rd row-carrying a bag and wearing a coat)

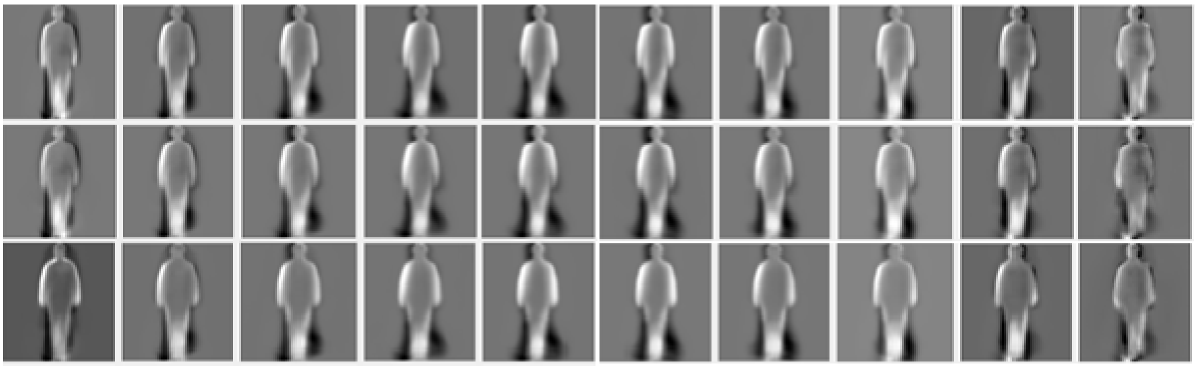
Figure 7-1: Differentiate Silhouette based on appearances

7.1 Conclusion

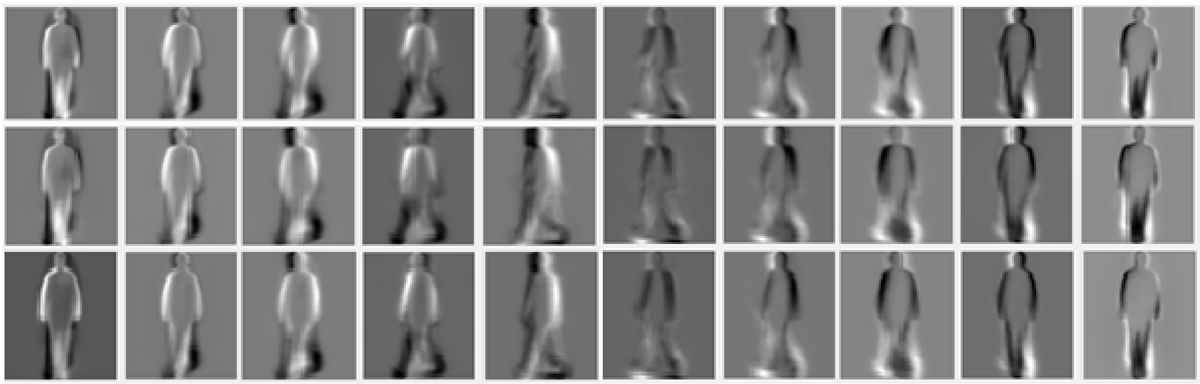
The first study is the basic gait representation which used four gait representations including Gait Energy Image (GEI), Gait Entropy Image (GEnI), Gait Gaussian Image (GGI) and Gait Gaussian Entropy Image (GGEnI). The observation from the results are the following:

- SVM is better than NN because SVM has more robustness to appearance changes.

- GEnI has the best correct classification rate (CCR) except the mixed appearance training which GEI has slightly better CCR than GEnI. This means GEI.
- If only one appearance is used for training, normal walking has a higher recognition rate. The difference between wearing a coat and carrying a bag is much greater than the difference between normal walking and the other appearance as it shows in Figure 7.1. This also shows the problem of appearance changes when training SVM with inadequate appearance dataset.



(a) The comparison between 0° and the other view angles (1st row-normal walking, 2nd row-carrying a bag, 3rd row-wearing a coat)



(b) The comparison between adjacent view angles (1st row-normal walking, 2nd row-carrying a bag, 3rd row-wearing a coat)

Figure 7-2: Differentiate Silhouette based on appearances view angles

- When only normal walking is trained in gait recognition by identical view, two view angles which frequently has average high recognition rate are 18° and 180°. At nearly 0° and 180°, the CCR of carrying a bag has a higher recognition rate because the bag has less effect on silhouettes especially the backpack type. Wearing a coat is the main problem in this dataset because the coat covers a larger region than a bag on CASIA dataset B. Especially, 0° and 180° has lower CCR than the other view angles. Two normal walking datasets as gallery samples are the minimum suggestion because the CCR between one and two training datasets is the biggest gap.

- Gaussian techniques are suitable for view classification and GGEnI has the highest view classification rate.

The second study is the secondary gait representation which is generated from basic gait representation in the first study. The three kinds of secondary include Convolutional Gait Image (CGI), Gradient Histogram Gait Image (GHCI) and Convolutional Gradient Histogram Gait Image (CGHGI) are introduced. The observation from the results are the following:

- When CNN is used as a multiclass classifier. The result shows the extracted feature between CNN layers with SVM having the better CCR rate than the CCR from CNN classifier. The feature from single convolutional with normalization block has the better recognition rate than full architecture CNN and it also has the same CCR level with the best CCR from the extracted feature between CNN layers. Thus, single convolutional with normalization block is adequate for SVM multiclass classifier. CNN has a low recognition rate when the number of training samples per class or subject is inadequate. Thus, many researchers train their CNN classifier as a binary classifier which gives the similarity or matching score between probe and gallery on gait recognition instead of the multi-class classifier.
- Convolutional techniques can slightly improve the CCR and it still has lower CCR on appearance changes especially with wearing a coat. While HOG technique can enormously improve the CCR. However, the suitable HOG parameters need to optimize for the best CCR. These optimal parameters are depended on each data sample. The optimal parameters on four normal walking training are cell size 2x2, block size 3x3 and 15 orientation bins.

- Entropy technique removes unnecessary information from gait representation while HOG technique divides images into several local regions by block and cell size parameter then the local features are combined as HOS features. From the GHGI results show that the gait representation without entropy techniques has higher CCR than gait representation with entropy technique. This means the unnecessary information which is removed by entropy techniques has some effect in HOG features.
- HOG also improves the CCR in view classification and GHGI-GGI has the best CCR.

Table 7-1: The comparison between average and maximum CCR of CGI and CGHGI

Representation		Appearance	Average	Max	Max-Average
CGI	D1	Normal	99.11%	99.14%	0.02%
		Bag	71.27%	74.61%	3.34%
		Coat	55.22%	57.29%	2.07%
		Average	75.20%	77.01%	1.81%
	D2	Normal	99.32%	99.33%	0.02%
		Bag	79.19%	82.64%	3.45%
		Coat	62.56%	65.99%	3.42%
		Average	80.36%	82.65%	2.30%
	D3	Normal	99.38%	99.57%	0.19%
		Bag	81.10%	87.30%	6.21%
		Coat	64.97%	70.22%	5.25%
		Average	81.82%	85.70%	3.88%
GHGI	E1	Normal	98.59%	99.63%	1.04%
		Bag	92.08%	93.14%	1.06%
		Coat	88.36%	88.37%	0.01%
		Average	93.01%	93.65%	0.64%
	E2	Normal	98.55%	98.90%	0.35%
		Bag	91.65%	92.01%	0.35%
		Coat	87.46%	88.21%	0.74%
		Average	92.55%	93.04%	0.48%
	E3	Normal	98.67%	99.70%	1.03%
		Bag	91.73%	91.89%	0.16%
		Coat	88.52%	89.21%	0.69%
		Average	92.97%	93.60%	0.62%

- CGI has higher CCR than basic gait representation however it is very close. While CGHGI has slightly lower CCR than GHGI. Each experiment is repeated five times. If each time is separately determined, the maximum CCR of CGI is much better than average CCR from five times. The comparison between average CCR and the maximum recognition rate is shown in

Table 7.1. Both CGI and CGHGI use GEI as basic representation. The CGHGI CCR maximum and average is very close but the CGI CCR maximum and average is explicitly different especially CGI D3. This because the random filter is used as a convolutional input parameter in this study. This means the output CGI and CGHGI is random as well. If the filter is optimized, the CCR for both CGI and CGHGI are probably much improved.

The third study is a partial body which divides silhouette into fourteen parts based on height. The observation from the results are as follows:

- When SVM is trained by normal walking samples, full body is the most effective part for most appearances and gait representations especially HOG representations. The lower knee is the best part when HOG technique is not involved. The full body always has the best CCR for normal walking samples. Part 4 (head to chest) is the best CCR in case of carrying a bag when using GEI. While part 11 (lower knee) has the best CCR in case of wearing a coat when using GEI and GEnI.
- The body part has lower CCR when testing with the other appearances, while part 7 (chin to finger) is the second-best parts when testing with normal walking appearance except GEI representation (part 9). The differential silhouette also shows this problem in Figure 7.1.
- If a low CCR GEI parts are considered together. The normal appearance has low CCR with chest to waist region from the CCR of part 3 and 5. The walking with a bag has low CCR with chest to knee region from the CCR of part 4 to part 12. Wearing a coat has low CCR with chin to knee from the CCR of part 3 to part 12. Because the affecting region of a coat is bigger than that of a bag. Thus, the coat has more effect to CCR rate on CASIA dataset B.
- The fusion parts which have higher CCR with each appearance should increase the overall CCR. As it can be seen from GEI and CGI results. The best part of both representations is not part 1 or full body but it is part 11- lower knee and part 12 - ankle followed by part 2 - head for GEI and part 1 for CGI. When both part 11 and part 12 are fused, the overall CCT rate is

increased. As it can be seen in PSF/PIF/MRD GEI and CGI fusion 5, 6, 9, 10, 13, 14. Even PIF GEI fusion 5, 6, 13, 14 has lower CCR than GEI single part 11 and part 12. However, the CCR is increased when the ratio of the second part is increased as it can be seen in MRD results. And CGI showed a big improvement with the image fusion as it can be seen from MRD 1:4 when comparing with a single part.

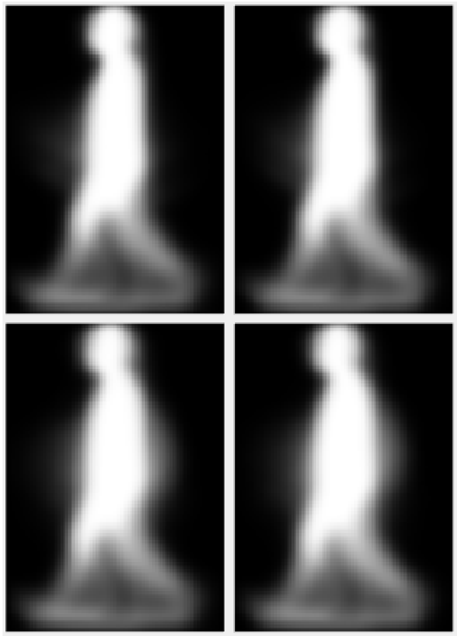
- With HOG technique, gait representation has more robustness on appearance changes. Thus, all single parts have better CCR compared to GEI and CGEI. Especially, full body has the best CCR. Part 3, 5, 6, 7 and 8 which is under the coverage region of bag and coat still has less CCR than part 2, 4, 9, 10, 11 and 12. Because the full body has all parts and the most robustness on appearance change thus the fusion between part 1 and the other part usually has lower CCR than an only full body part. Part 9, 10 and 4 is the best second to four single part with HOG. Part 4 has more robustness on walking with a bag while part 8 and 9 have more robustness with wearing a coat. The fusion of these three parts has better CCR as it can be seen from PSF/PIF/MRD GHGI and CGHGI fusion 11 and 12. PSF GHGI and CGHGI have the best CCR when compared with PIF and MRD especially fusion 12 (head to chest and lower hip) has higher CCR than full body. And the second part of the ratio increasing has a worse result with HOG technique thus only PIF is suggested to use with GHGI and CGHGI.
- The best part for view classification is part 11 or lower knee followed by part 10. If the full silhouette is considered, the most movement within a region is the lower body as it can be seen in Figure 7.2. And the movement of this region also the most varied region when the camera view angle is changed. Without HOG technique, GGEnI has the best CCR for view classification. And HOG technique also improves the appearance change robustness thus HOG also improves the overall CCR. As it’s mentioned before, HOG technique has more effect on gait representations without entropy technique. The GHGI-GGI CCR beats the GHGI-GGEnI. GHGI-GGI part 10 is the best representation for view classification on CASIA dataset B.

- HOG technique also increased the recognition rate in cross view recognition. The best part for cross view recognition with GHGI is part 1 or full body followed by part 7 or chin to finger. Part 7 is one of the parts of the body area which has fewer changes compared with the other body regions as it can be seen in Figure 7.2. This means the silhouette shape of the body part in every view angle is quite similar. Although the CCR of parts in the body region is dropped when they are testing with a probe from the different view angle. The CCR of parts within the other region is much more reduced when they are testing with a probe from different view angles.
- The personal models generated by linear SVM are suitable for cross view recognition. As it can be seen, all gait representations have higher recognition rates in cross view recognition when compared to the other publication.

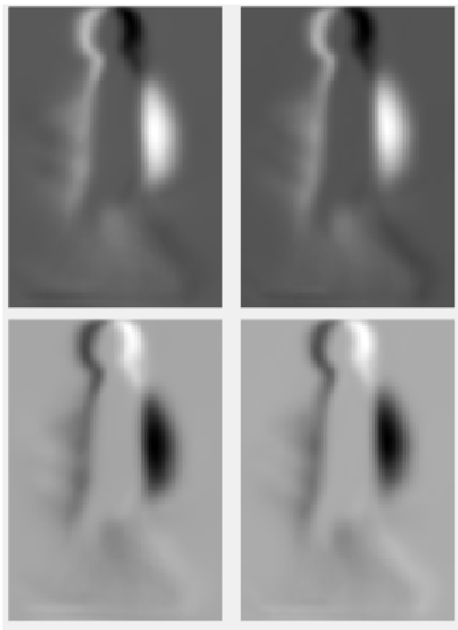
The fourth study is gait recognition under the large data samples. OU-ISIR Large Population dataset with Bag β version (OU-LP-Bag β) is chosen. The observation from the results are the following:

- In the case of a single part, part 1 or full body always had the best CCR for all gait representations. As it can be seen from the CCR results and the difference of probe and gallery in Figure 7.3, lower body is less affected by carrying a bag especially lower knee region. The upper body has a lower CCR.
- Under the various kinds of bag and carrying postures, the combined approach has more reliability than a single part. Most PSF and PIF fusion has higher CCR than the CCR of two selected parts.
- If GEI full body is excluded, GEI part 11 and 12 had higher CCR than the other parts. When both parts are fused with the other part, the CCR of part fusions is greatly higher than the CCR of the full body. MRD has higher CCR than PIF especially when the second part ratio is increased. And fusion 12 (part 2 and part 12) has the highest CCR followed by fusion 11 (part 2 and part 11). The chest to lower knee region which has less problem from the effect of

carrying a bag are used in both fusions. Fusion 1 to 7 should use PSF technique because the recognition rate is reduced when the second part ratio is increased.



(a) The average all dataset GEI (left is training dataset, right is testing dataset, top is normal walking or gallery and bottom is carrying a bag or probe)



(b) The different between Gallery and Probe samples (first row is probe-gallery, second row is gallery-probe, left is training dataset and right is testing dataset)

Figure 7-3: Average OU-LP-Bag dataset GEI and the differential between the gallery and probe samples

- HOG technique improves the robustness on bag carrying especially for part 1, 9 and 10 where their CCR improved by more than 20%. Both GHGI and CGHGI should use PIF technique for part fusion. HOG technique is not suitable for MRD because the CCR is reduced when the number of the second part ratio is increased. In case of PSF, part 1 had higher CCR when it is fused with part 9, 10, 11 and 12. GHGI fusion 3 (part 1 and 10) which used two of three best improving parts by HOG has the best CCR.

7.2 Contributions

The main contributions of this study are as follows:

- Developed an effective general gait recognition framework which uses gait compact image as input, extracted gait features with the optimal feature map by PCA and one-against-all linear SVM classifier. This framework can solve three problems including gait recognition by identical view, view angle classification, and cross view gait recognition.
- Create new gait representations including Gait Gaussian Entropy Image (GGEnI) which is suitable for view classification duty, Convolutional Gait Image (CGI) which slightly improves overall CCR of basic gait representation and Convolutional Gradient Histogram Gait Image (CGHGI) which greatly improves the robustness for appearance changes.
- Prove the effectiveness of various fusion for human body parts in partial body gait recognition. The most effective fusion part for basic gait representation is lower knee followed by ankle. When HOG technique is involved, full body becomes the most effective part followed by limb and lower hip. If full silhouette cannot be taken into account, there are several fusions which should be used, i.e. fusion of part 4-head to chest and part 11-lower knee, and fusion of part 4 and part 12-ankle for GEI and CGI, fusion of part 4 and part 9-limb and fusion of part 4 and part 10-lower hip for GHGI and CGHGI.
- Develop various fusion techniques including Part Score Fusion (PSF), Part Image Fusion (PIF) and Multi Region Duplication (MRD). GEI, GEnI, GGI, GGEnI, and CGI suggests using MRD 1:4

for their best recognition with a fusion of part 4 and part 11 or part 12. While GHGI and CGHGI suggest to used PSF for fusion of part 4 and part 9 or part 10 on CASIA dataset B and PIF for OU-LP-Bag β.

- Prove that the effective gait representation and framework for view angle classification which is GGEnI and GHGI-GGI. Both of them have high CCR comparing with the other publication especially GHGI-GGI parts 10 and 11.
- Prove the effectiveness of gait representation and framework for cross view gait recognition. The output CCR shows better performance when comparing with the other publication especially GHGI-GGI.

7.3 Future work

This study has focused on gait recognition in respect to camera view angles and appearance changes caused by coats and bags with two standard gait databases. However, there are still many areas which can be explored to extend this study.

- In the convolution-based secondary gait representation, the optimal filter for CGI and CGHGI may potentially improve the gait recognition performance. This study uses the randomized filters as convolutional blocks which makes a random result as well. However, the average recognition rate of both representations is still high. If all experiments have been determined, CGI result is usually better than its corresponding basic gait representation and CGHGI result is sometimes better than GHGI as it can be seen in Table 7.1. This means there are some aspects that can improve the recognition rate of both representations. If the filter can be optimized for gait recognition, the recognition should be higher than the result of this study.
- There are many challenges in gait recognition and there is the number of standard gait databases. The proposed gait representation and gait recognition framework may be tested

by other gait databases especially OU-ISIR Treadmill dataset B (cloth variation) and OU-ISIR Multi-view Large population dataset for its generalization.

- The large population gait recognition is still the main problem which can be seen from the recognition rate under OU-LP-Bag dataset. When the number of class and the human action variations are increased, the CCR greatly dropped. OU-LP-Bag has only one training sample per subjects while this study suggests at least two training samples per subject for multiclass classification. More approaches and techniques are needed to improve real-world applications.
- The automatic gait recognition system should be addressed. In this study, view angle classification, gait recognition by identical view and cross view gait recognition are studied. However, a system combining the three aspects needs more configurations and optimization to improve the gait recognition performance.
- Experiment on the high-performance computing environments. Because this experiment experienced some device limitations, thus some configurations could not be used as it is mentioned in Chapter 5. Also, special GPU can boost up both computing speed and detail of image processing information which may possibly change the final output CCR.

References

1. Dinca, L.M. and G.P. Hancke, *The Fall of One, the Rise of Many: A Survey on Multi-Biometric Fusion Methods.* IEEE Access, 2017. 5: p. 6247-6289.
2. Chattopadhyay, P., S. Sural, and J. Mukherjee, *Frontal Gait Recognition From Incomplete Sequences Using RGB-D Camera.* Information Forensics and Security, IEEE Transactions on, 2014. 9(11): p. 1843-1856.
3. Putz-Leszczynska, J. and M. Granacki. *Gait biometrics with a Microsoft Kinect sensor*. in *Security Technology (ICCST), 2014 International Carnahan Conference on*. 2014.
4. Borelli, G.A. and P. Maquet, *On the Movement of Animals*. 2012: Springer Berlin Heidelberg.
5. Weber, W.E., et al., *Mechanics of the Human Walking Apparatus*. 1992: Springer-Verlag.
6. Braune, W. and O. Fischer, *The human gait*. 1987: Springer-Verlag.
7. Kory, M.P.M.A.B.D.R.C., *Walking patterns of normal men.* Journal of Bone and Joint Surgery, 1964. 46(2): p. 335-360.
8. Niyogi, S.A. and E.H. Adelson. *Analyzing gait with spatiotemporal surfaces*. in *Proceedings of 1994 IEEE Workshop on Motion of Non-rigid and Articulated Objects*. 1994.
9. Phillips, P.J., et al. *The gait identification challenge problem: data sets and baseline algorithm*. in *Object recognition supported by user interaction for service robots*. 2002.
10. Sarkar, S., et al., *The humanID gait challenge problem: data sets, performance, and analysis.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 2005. 27(2): p. 162-177.
11. Ralph, G.J., Shi, *The CMU Motion of Body (mobo) Database Technical Report*. 2001, Robotic Institute, Carnegie Mellon University.
12. Nixon, M., *Southampton Gait Database*. 2000, University of Southampton.
13. Connor, P. and A. Ross, *Biometric recognition by gait: A survey of modalities and features.* Computer Vision and Image Understanding, 2018. 167: p. 1-27.

14. Gadaleta, M. and M. Rossi, *IDNet: Smartphone-based gait recognition with convolutional neural networks.* Pattern Recognition, 2018. 74: p. 25-37.

15. Muaaz, M. and R. Mayrhofer, *Smartphone-Based Gait Recognition: From Authentication to Imitation.* IEEE Transactions on Mobile Computing, 2017. 16(11): p. 3209-3221.

16. Sprager, S. and M.B. Juric, *An Efficient HOS-Based Gait Authentication of Accelerometer Data.* IEEE Transactions on Information Forensics and Security, 2015. 10(7): p. 1486-1498.

17. Al-Naffakh, N., et al. *Unobtrusive Gait Recognition Using Smartwatches*. in *2017 International Conference of the Biometrics Special Interest Group (BIOSIG)*. 2017.

18. Kork, S.K.A., et al. *Biometric database for human gait recognition using wearable sensors and a smartphone*. in *2017 2nd International Conference on Bio-engineering for Smart Technologies (BioSMART)*. 2017.

19. Dikovski, B., G. Madjarov, and D. Gjorgjevikj. *Evaluation of different feature sets for gait recognition using skeletal data from Kinect*. in *Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2014 37th International Convention on*. 2014.

20. Ngo, T.T., et al., *Similar gait action recognition using an inertial sensor.* Pattern Recognition, 2015. 48(4): p. 1289-1301.

21. Sulovská, K., et al., *Appropriateness of gait analysis for biometrics: Initial study using FDA method.* Measurement, 2017. 105: p. 1-10.

22. Attal, F., et al., *Automatic Recognition of Gait phases Using a Multiple Regression Hidden Markov Model.* IEEE/ASME Transactions on Mechatronics, 2018: p. 1-1.

23. Zou, Q., et al., *Robust Gait Recognition by Integrating Inertial and RGBD Sensors.* IEEE Transactions on Cybernetics, 2018. 48(4): p. 1136-1150.

24. Sun, B., et al., *Self-esteem recognition based on gait pattern using Kinect.* Gait & Posture, 2017. 58: p. 428-432.

25. Sharma, D.G., I. Tanev, and K. Shimohara. *Analysis of genetic programming in gait recognition*. in *Evolutionary Computation (CEC), 2015 IEEE Congress on*. 2015.

26. Yam, C., M.S. Nixon, and J.N. Carter, *Automated person recognition by walking and running via model-based approaches.* Pattern Recognition, 2004. 37(5): p. 1057-1072.

27. BenAbdelkader, C., R. Cutler, and L. Davis. *Person identification using automatic height and stride estimation*. in *Pattern Recognition, 2002. Proceedings. 16th International Conference on*. 2002.

28. BenAbdelkader, C., R. Cutler, and L. Davis. *Stride and cadence as a biometric in automatic person identification and verification*. in *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on*. 2002.

29. Ng, H., et al., *Development of Vision Based Multiview Gait Recognition System with MMUGait Database.* The Scientific World Journal, 2014. 2014: p. 13.

30. Kang, Z., M. Deng, and C. Wang. *Frontal-view human gait recognition based on Kinect features and deterministic learning*. in *2017 36th Chinese Control Conference (CCC)*. 2017.

31. Liu, Z. and S. Sarkar. *Simplest representation yet for gait recognition: averaged silhouette*. in *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*. 2004.

32. Han, J. and B. Bhanu, *Individual recognition using gait energy image.* Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2006. 28(2): p. 316-322.

33. Bashir, K., X. Tao, and G. Shaogang. *Gait recognition using Gait Entropy Image*. in *Crime Detection and Prevention (ICDP 2009), 3rd International Conference on*. 2009.

34. Zhang, E., Y. Zhao, and W. Xiong, *Active energy image plus 2DLPP for gait recognition.* Signal Processing, 2010. 90(7): p. 2295-2302.

35. Yang, Y., D. Tu, and G. Li. *Gait Recognition Using Flow Histogram Energy Image*. in *Pattern Recognition (ICPR), 2014 22nd International Conference on*. 2014.

36. Arora, P. and S. Srivastava. *Gait recognition using gait Gaussian image*. in *Signal Processing and Integrated Networks (SPIN), 2015 2nd International Conference on*. 2015.

37. Arora, P., et al., *Improved Gait Recognition Using Gradient Histogram Gaussian Image.* Procedia Computer Science, 2015. 58: p. 408-413.

38. Bo, Y. and Y. Wen. *A New Gait Recognition Method Based on Body Contour*. in *Control, Automation, Robotics and Vision, 2006. ICARCV '06. 9th International Conference on*. 2006.

39. Zeng, W., C. Wang, and F. Yang, *Silhouette-based gait recognition via deterministic learning.* Pattern Recognition, 2014. 47(11): p. 3568-3584.

40. Rokanujjaman, M., et al., *Effective part-based gait identification using frequency-domain gait entropy features.* Multimedia Tools and Applications, 2015. 74(9): p. 3099-3120.

41. Rokanujjaman, M., M.A. Hossain, and M.R. Islam. *Effective part selection for part-based gait identification*. in *2012 7th International Conference on Electrical and Computer Engineering*. 2012.

42. Islam, M.S., et al. *A new effective part selection approach for part-based gait recognition*. in *16th Int'l Conf. Computer and Information Technology*. 2014.

43. Rokanujjaman, M., et al. *Part definition and selection for part-based speed invariant gait recognition*. in *2016 9th International Conference on Electrical and Computer Engineering (ICECE)*. 2016.

44. Yeoh, T.W., et al., *On the effectiveness of feature selection methods for gait classification under different covariate factors.* Applied Soft Computing, 2017. 61: p. 42-57.

45. Shaikh, S.H., K. Saeed, and N. Chaki. *Gait recognition using partial silhouette-based approach*. in *Signal Processing and Integrated Networks (SPIN), 2014 International Conference on*. 2014.

46. Rida, I., X. Jiang, and G.L. Marcialis, *Human Body Part Selection by Group Lasso of Motion for Model-Free Gait Recognition.* IEEE Signal Processing Letters, 2016. 23(1): p. 154-158.

47. Yang, F., L. Yuncheng, and L. Jiebo. *Learning effective Gait features using LSTM*. in *2016 23rd International Conference on Pattern Recognition (ICPR)*. 2016.

48. Winter, D.A., *The Biomechanics and Motor Control of Human Movement, 4th Edition*. 2009: John Wiley & Sons. 384.

49. Nandy, A., et al. *Gait identification using component based gait energy image analysis*. in *Signal Propagation and Computer Technology (ICSPCT), 2014 International Conference on*. 2014.

50. Aggarwal, H. and D.K. Vishwakarma, *Covariate Conscious Approach for Gait Recognition Based Upon Zernike Moment Invariants.* IEEE Transactions on Cognitive and Developmental Systems, 2018. 10(2): p. 397-407.

51. Rokanujjaman, M., M.A. Hossain, and M.A. Hossin. *Part-based gait identification using fusion technique*. in *Informatics, Electronics & Vision (ICIEV), 2014 International Conference on*. 2014.

52. Cover, T. and P. Hart, *Nearest neighbor pattern classification.* IEEE Transactions on Information Theory, 1967. 13(1): p. 21-27.

53. Arora, P., M. Hanmandlu, and S. Srivastava, *Gait based authentication using gait information image features.* Pattern Recognition Letters, 2015. 68, Part 2: p. 336-342.

54. Mahfouf, Z., et al., *Investigating the use of motion-based features from optical flow for gait recognition.* Neurocomputing, 2018. 283: p. 140-149.

55. Chaurasia, P., et al., *Fusion of Random Walk and Discrete Fourier Spectrum Methods for Gait Recognition.* IEEE Transactions on Human-Machine Systems, 2017. 47(6): p. 751-762.

56. Karamizadeh, S., et al. *Advantage and drawback of support vector machine functionality*. in *2014 International Conference on Computer, Communications, and Control Technology (I4CT)*. 2014.

57. Hanmin, Y. and H. Peiliang. *Gait recognition based on feature fusion and support vector machine*. in *2016 IEEE International Conference of Online Analysis and Computing Science (ICOACS)*. 2016.

58. Chetty, G., et al. *Multiview gait biometrics for human identity recognition*. in *Computing for Sustainable Global Development (INDIACom), 2014 International Conference on*. 2014.

59. Prakash, C., et al. *A framework for human recognition using a multimodel Gait analysis approach*. in *2016 International Conference on Computing, Communication and Automation (ICCCA)*. 2016.

60. Bajwa, T.K., S. Garg, and K. Saurabh. *GAIT analysis for identification by using SVM with K-NN and NN techniques*. in *2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC)*. 2016.

61. Yeoh, T., H.E. Aguirre, and K. Tanaka. *Clothing-invariant gait recognition using convolutional neural network*. in *2016 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*. 2016.

62. Shiraga, K., et al. *GEINet: View-invariant gait recognition using a convolutional neural network*. in *2016 International Conference on Biometrics (ICB)*. 2016.

63. Alotaibi, M. and A. Mahmood, *Improved gait recognition based on specialized deep convolutional neural network.* Computer Vision and Image Understanding, 2017. 164: p. 103-110.

64. Rauf, M., et al. *Knowledge transfer between networks and its application on gait recognition*. in *2016 IEEE International Conference on Digital Signal Processing (DSP)*. 2016.

65. He, Y., et al., *Multi-Task GANs for View-Specific Feature Learning in Gait Recognition.* IEEE Transactions on Information Forensics and Security, 2019. 14(1): p. 102-113.

66. Chhatrala, R. and D.V. Jadhav, *Multilinear Laplacian discriminant analysis for gait recognition.* IET Computer Vision, 2017. 11(2): p. 153-160.

67. El-Alfy, H., I. Mitsugami, and Y. Yagi, *Gait Recognition Based on Normal Distance Maps.* IEEE Transactions on Cybernetics, 2018. 48(5): p. 1526-1539.

68. Medikonda, J., H. Madasu, and P.B. Ketan, *Information set based features for the speed invariant gait recognition.* IET Biometrics, 2018. 7(3): p. 269-277.

69. Alotaibi, M. and A. Mahmood, *Reducing covariate factors of gait recognition using feature selection and dictionary-based sparse coding.* Signal, Image and Video Processing, 2017. 11(6): p. 1131-1138.

70. Chhatrala, R., et al., *Sparse multilinear Laplacian discriminant analysis for gait recognition.* Pattern Analysis and Applications, 2017.

71. Deng, M., et al., *Fusion of spatial-temporal and kinematic features for gait recognition with deterministic learning.* Pattern Recognition, 2017. 67: p. 186-200.

72. Verlekar, T.T., P.L. Correia, and L.D. Soares, *View-invariant gait recognition system using a gait energy image decomposition method.* IET Biometrics, 2017. 6(4): p. 299-306.

73. Battistone, F. and A. Petrosino, *TGLSTM: A time based graph deep learning approach to gait recognition.* Pattern Recognition Letters, 2018.

74. Alotaibi, M. and A. Mahmood. *Improved Gait recognition based on specialized deep convolutional neural networks*. in *2015 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*. 2015.

75. Chhatrala, R. and D. Jadhav, *Gait recognition based on curvelet transform and PCANet.* Pattern Recognition and Image Analysis, 2017. 27(3): p. 525-531.

76. Lishani, A.O., et al. *Gabor filter bank-based GEI features for human Gait recognition*. in *2016 39th International Conference on Telecommunications and Signal Processing (TSP)*. 2016.

77. Luo, Z., T. Yang, and Y. Liu. *Gait optical flow image decomposition for human recognition*. in *2016 IEEE Information Technology, Networking, Electronic and Automation Control Conference*. 2016.

78. Guru, V.G.M., V.N. Kamalesh, and R. Dinesh. *Human gait recognition using four directional variations of gradient gait energy image*. in *2016 International Conference on Computing, Communication and Automation (ICCCA)*. 2016.

79. Zhang, C., et al. *Siamese neural network based gait recognition for human identification*. in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. 2016.

80. Lamar-Leon, J., et al. *Persistent homology-based gait recognition robust to upper body variations*. in *2016 23rd International Conference on Pattern Recognition (ICPR)*. 2016.

81. Yang, T., Z. Zeng, and X. Chen. *Gait recognition robust to dress and carrying using multi-link gravity center track*. in *Information and Automation, 2015 IEEE International Conference on*. 2015.

82. Yu, G., L. Chang-Tsun, and F. Roli, *On Reducing the Effect of Covariate Factors in Gait Recognition: A Classifier Ensemble Method.* Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2015. 37(7): p. 1521-1528.

83. Huang, S., et al., *Cross-Speed Gait Recognition Using Speed-Invariant Gait Templates and Globality–Locality Preserving Projections.* Information Forensics and Security, IEEE Transactions on, 2015. 10(10): p. 2071-2083.

84. Yogarajah, P., et al., *Enhancing gait based person identification using joint sparsity model and -norm minimization.* Information Sciences, 2015. 308: p. 3-22.

85. Zhang, L., et al., *A sparse and discriminative tensor to vector projection for human gait feature representation.* Signal Processing, 2015. 106: p. 245-252.

86. Lee, C.P., A.W.C. Tan, and S.C. Tan, *Gait recognition with Transient Binary Patterns.* Journal of Visual Communication and Image Representation, 2015. 33: p. 69-77.

87. Zeng, W. and C. Wang, *Gait recognition across different walking speeds via deterministic learning.* Neurocomputing, 2015. 152: p. 139-150.

88. Zhihui, L., et al., *Human Gait Recognition via Sparse Discriminant Projection Learning.* Circuits and Systems for Video Technology, IEEE Transactions on, 2014. 24(10): p. 1651-1662.

89. Yawei, T., et al. *Multilinear mean component analysis for gait recognition*. in *Control and Decision Conference (2014 CCDC), The 26th Chinese*. 2014.

90. Mohan Kumar, H.P. and H.S. Nagendraswamy. *LBP for gait recognition: A symbolic approach based on GEI plus RBL of GEI*. in *Electronics and Communication Systems (ICECS), 2014 International Conference on*. 2014.

91. Das Choudhury, S. and T. Tjahjadi, *Robust view-invariant multiscale gait recognition.* Pattern Recognition, 2015. 48(3): p. 798-811.

92. *CASIA Gait Database*. 14/09/2018]; Available from: http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp.

93. Zheng, S. *Gait Recognition*. 14/09/2018]; Available from: http://kylezheng.org/research-projects/gait-recognition/.

94. Makihara, Y., et al., *Gait Recognition: Databases, Representations, and Applications*, in *Encyclopedia of Electrical and Electronics Engineering*. 2015, Wiley.

95. Sugiura, Y.M.H.M.A.T.M.A.H.K., A. Mori, and Y. Yagi, *The OU-ISIR Gait Database Comprising the Treadmill Dataset.* IPSJ Trans. on Computer Vision and Applications, 2012. 4: p. 53-62.

96. Iwama, H., et al., *The OU-ISIR Gait Database Comprising the Large Population Dataset and Performance Evaluation of Gait Recognition.* IEEE Transactions on Information Forensics and Security, 2012. 7(5): p. 1511-1521.

97. Mansur, A., et al. *Gait Recognition under Speed Transition*. in *Computer Vision and Pattern Recognition (CVPR), 2014 IEEE Conference on*. 2014.

98. Ngo, T.T., et al., *The largest inertial sensor-based gait database and performance evaluation of gait-based personal authentication.* Pattern Recognition, 2014. 47(1): p. 228-237.

99. Uddin, M.Z., et al., *The OU-ISIR Large Population Gait Database with real-life carried object and its performance evaluation.* IPSJ Transactions on Computer Vision and Applications, 2018. 10(1): p. 5.

100. Makihara, N.T.Y., et al., *Multi-view large population gait dataset and its performance evaluation for cross-view gait recognition.* IPSJ Trans. on Computer Vision and Applications, 2018. 10(4): p. 1-14.

101. Xu, C., et al., *The OU-ISIR Gait Database comprising the Large Population Dataset with Age and performance evaluation of age estimation.* IPSJ Transactions on Computer Vision and Applications, 2017. 9(1): p. 24.

102. Yu, S., D. Tan, and T. Tan. *A Framework for Evaluating the Effect of View Angle, Clothing and Carrying Condition on Gait Recognition*. in *Pattern Recognition, 2006. ICPR 2006. 18th International Conference on*. 2006.

103. Bashir, K., T. Xiang, and S. Gong, *Gait recognition without subject cooperation.* Pattern Recognition Letters, 2010. 31(13): p. 2052-2060.

104. Hu, M., et al., *Incremental Learning for Video-Based Gait Recognition With LBP Flow.* IEEE Transactions on Cybernetics, 2013. 43(1): p. 77-89.

105. Jeevan, M., et al. *Gait recognition based on gait pal and pal entropy image*. in *2013 IEEE International Conference on Image Processing*. 2013.

106. Dupuis, Y., X. Savatier, and P. Vasseur, *Feature subset selection applied to model-free gait recognition.* Image and Vision Computing, 2013. 31(8): p. 580-591.

107. Kusakunniran, W., *Recognizing Gaits on Spatio-Temporal Feature Domain.* Information Forensics and Security, IEEE Transactions on, 2014. 9(9): p. 1416-1423.

108. Rida, I., et al. *Improved Human Gait Recognition*. in *Image Analysis and Processing — ICIAP 2015*. 2015. Cham: Springer International Publishing.

109. Rida, I., S.A. Maadeed, and A. Bouridane. *Unsupervised feature selection method for improved human gait recognition*. in *2015 23rd European Signal Processing Conference (EUSIPCO)*. 2015.

110. Rida, I., et al. *Robust model-free gait recognition by statistical dependency feature selection and Globality-Locality Preserving Projections*. in *2016 39th International Conference on Telecommunications and Signal Processing (TSP)*. 2016.

111. Rida, I., S. Almaadeed, and A. Bouridane, *Gait recognition based on modified phase-only correlation.* Signal, Image and Video Processing, 2016. 10(3): p. 463-470.

112. Alotaibi, M. and A. Mahmood. *Reduction of Gait Covariate Factors Using Feature Selection and Sparse Dictionary Learning*. in *2016 IEEE International Symposium on Multimedia (ISM)*. 2016.

113. Bashir, K., T. Xiang, and S. Gong. *Gait Representation Using Flow Fields*. in *BMVC*. 2009.

114. Wang, C., et al., *Human Identification Using Temporal Information Preserving Gait Template.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 2012. 34(11): p. 2164-2176.

115. Kusakunniran, W., *Attribute-based learning for gait recognition using spatio-temporal interest points.* Image and Vision Computing, 2014. 32(12): p. 1117-1126.

116. Makihara, Y., et al. *Joint Intensity and Spatial Metric Learning for Robust Gait Recognition*. in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2017.

117. Zheng, S., et al., *Robust View Transformation Model for Gait Recognition.* 2011 18th Ieee International Conference on Image Processing (Icip), 2011.

118. Burges, C.C., *A Tutorial on Support Vector Machines for Pattern Recognition.* Data Mining and Knowledge Discovery, 1998. 2(2): p. 121-167.

119. Chang, C.-C. and C.-J. Lin, *LIBSVM: A library for support vector machines.* ACM Trans. Intell. Syst. Technol., 2011. 2(3): p. 1-27.

120. Vedaldi, A.L., K. . *MatConvNet -- Convolutional Neural Networks for MATLAB*. in *Multimedia*. 2015. ACM.

121. Hofmann, M. and G. Rigoll. *Improved Gait Recognition using Gradient Histogram Energy Image*. in *2012 19th IEEE International Conference on Image Processing*. 2012.

122. Dalal, N. and B. Triggs. *Histograms of oriented gradients for human detection*. in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*. 2005.

123. Whytock, T., A. Belyaev, and N.M. Robertson, *On covariate factor detection and removal for robust gait recognition.* Machine Vision and Applications, 2015. 26(5): p. 661-674.

124. Bashir, K., T. Xiang, and S. Gong. *Cross View Gait Recognition Using Correlation Strength*. in *BMVC*. 2010.

125. Verlekar, T.T. and P.L. Correia. *Walking direction identification using perceptual hashing*. in *2016 4th International Conference on Biometrics and Forensics (IWBF)*. 2016.

126. Haifeng, H., *Multiview Gait Recognition Based on Patch Distribution Features and Uncorrelated Multilinear Sparse Local Discriminant Canonical Correlation Analysis.* Circuits and Systems for Video Technology, IEEE Transactions on, 2014. 24(4): p. 617-630.

127. Verlekar, T., P. Correia, and L. Soares. *View-Invariant Gait Recognition Exploiting Spatio-Temporal Information and a Dissimilarity Metric*. in *2016 International Conference of the Biometrics Special Interest Group (BIOSIG)*. 2016.

128. Li, W., C.C.J. Kuo, and J. Peng, *Gait recognition via GEI subspace projections and collaborative representation classification.* Neurocomputing, 2018. 275: p. 1932-1945.

129. Castro, F.M., et al., *Fisher Motion Descriptor for Multiview Gait Recognition.* International Journal of Pattern Recognition and Artificial Intelligence, 2017. 31(01): p. 1756002.

Appendix A - Chapter 3 Additional Results

A.1 CCR of four normal walking training

			View Angle											
			0	18	36	54	72	90	108	126	144	162	180	Average
Without PCA	GEI	Normal	99.57	100.00	99.57	98.71	98.71	99.14	99.14	99.14	98.71	98.71	99.14	99.14
		Bag	77.76	72.76	76.29	65.43	66.29	67.84	71.72	68.88	70.86	72.50	79.66	71.82
		Coat	47.59	57.93	55.78	61.03	57.07	59.14	57.59	53.02	54.22	52.76	51.55	55.24
		Mixed	74.97	76.90	77.21	75.06	74.02	75.37	76.15	73.68	74.60	74.66	76.78	75.40
	GEnI	Normal	99.14	99.57	99.57	99.31	99.57	99.14	98.71	99.05	98.71	98.71	99.14	99.15
		Bag	84.48	83.79	80.95	76.98	78.62	78.10	79.40	77.67	79.22	82.93	86.72	80.81
		Coat	59.83	65.09	63.19	65.26	60.78	53.79	55.43	58.62	60.26	62.93	56.72	60.17
		Mixed	81.15	82.82	81.24	80.52	79.66	77.01	77.84	78.45	79.40	81.52	80.86	80.04
	GGI	Normal	100.00	100.00	99.14	99.14	98.71	99.14	98.02	98.71	98.45	99.14	99.57	99.09
		Bag	62.24	62.07	51.55	46.72	35.69	35.43	35.09	40.86	45.26	54.14	61.47	48.23
		Coat	20.69	29.66	29.91	30.17	31.55	35.52	30.69	33.71	30.00	27.50	27.84	29.75
		Mixed	60.98	63.91	60.20	58.68	55.32	56.70	54.60	57.76	57.90	60.26	62.96	59.02
	GHGI	Normal	100.00	100.00	99.14	99.14	98.71	98.28	98.10	98.71	98.10	99.57	99.14	98.99
		Bag	70.34	66.47	59.91	53.71	52.93	56.55	52.67	51.38	52.76	57.50	70.52	58.61
		Coat	35.52	29.22	34.31	32.16	33.02	33.19	31.47	31.90	29.31	27.76	38.53	32.40
		Mixed	68.62	65.23	64.45	61.67	61.55	62.67	60.75	60.66	60.06	61.61	69.40	63.33
With PCA	GEI	Normal	99.57	100.00	99.57	98.71	98.71	99.14	99.14	99.14	98.71	98.71	99.14	99.14
		Bag	77.07	72.59	76.55	66.03	66.03	67.50	70.69	68.71	71.21	72.41	79.83	71.69
		Coat	47.76	58.36	55.26	60.78	57.93	59.48	58.53	54.05	53.88	51.90	51.90	55.44
		Mixed	74.80	76.98	77.13	75.17	74.22	75.37	76.12	73.97	74.60	74.34	76.95	75.42
	GEnI	Normal	99.14	99.57	99.57	99.22	99.57	99.14	98.71	99.14	98.71	98.71	99.14	99.15
		Bag	84.05	83.79	81.29	76.98	78.62	77.93	79.48	77.50	79.05	83.36	86.81	80.81
		Coat	59.83	64.66	63.53	65.00	60.95	53.71	54.91	58.45	60.26	62.67	56.55	60.05
		Mixed	81.01	82.67	81.47	80.40	79.71	76.93	77.70	78.36	79.34	81.58	80.83	80.00
	GGI	Normal	100.00	100.00	99.14	99.14	98.71	99.14	98.02	98.71	98.36	99.14	99.57	99.08
		Bag	62.24	62.41	51.38	46.03	35.26	34.48	34.91	40.78	45.34	53.79	61.12	47.98
		Coat	20.86	29.48	30.09	29.91	31.72	36.38	30.78	33.88	30.43	26.98	27.41	29.81
		Mixed	61.03	63.97	60.20	58.36	55.23	56.67	54.57	57.79	58.05	59.97	62.70	58.96
	GHGI	Normal	100.00	100.00	99.14	99.05	98.71	98.02	98.10	98.71	97.93	99.57	99.14	98.94
		Bag	70.17	66.64	59.83	53.28	53.19	56.64	52.59	52.16	52.67	57.84	70.95	58.72
		Coat	35.78	29.40	34.05	31.72	33.53	33.45	31.55	31.90	29.40	28.10	38.28	32.47
		Mixed	68.65	65.34	64.34	61.35	61.81	62.70	60.75	60.92	60.00	61.84	69.45	63.38

A.2 CCR when training with different appearance

			View Angle											
			0	18	36	54	72	90	108	126	144	162	180	Average
Carrying a bag	GEI	Normal	68.99	62.56	55.34	52.84	55.75	55.49	53.62	49.74	52.82	61.12	67.13	57.76
		Bag	92.24	88.28	89.66	89.31	91.90	93.10	93.10	93.97	93.10	92.24	93.79	91.88
		Coat	29.31	35.43	33.88	40.00	43.19	39.91	35.86	32.50	36.55	31.98	31.90	35.50
		Mixed	63.52	62.09	59.63	60.72	63.61	62.84	60.86	58.74	60.82	61.78	64.27	61.72

		Normal	67.36	71.26	62.82	61.64	61.81	61.81	62.30	60.17	61.18	68.19	66.81	64.12
		Bag	92.76	92.07	90.34	91.03	93.10	95.17	97.59	95.00	93.28	92.41	93.97	93.34
		Coat	38.97	44.48	46.12	44.40	45.43	41.38	39.83	44.31	40.60	40.17	36.47	42.01
	GEnI	Mixed	66.36	69.27	66.43	65.69	66.78	66.12	66.57	66.49	65.02	66.93	65.75	66.49
		Normal	58.22	48.79	37.67	37.10	36.52	37.04	38.91	34.68	30.49	46.52	59.34	42.30
		Bag	91.38	86.21	85.17	87.59	86.72	88.97	87.93	84.48	85.52	86.72	90.17	87.35
		Coat	11.90	17.67	17.41	16.55	11.12	10.52	12.07	13.36	14.05	12.07	11.03	13.43
	GGI	Mixed	53.83	50.89	46.75	47.08	44.79	45.51	46.30	44.18	43.35	48.44	53.52	47.69
		Normal	59.05	52.27	45.98	43.33	36.64	37.59	42.50	36.26	38.82	47.79	60.60	45.53
		Bag	91.55	87.76	87.41	87.07	86.21	88.10	85.00	84.31	86.55	87.93	89.66	87.41
		Coat	17.59	14.74	17.84	17.33	14.31	11.55	15.69	15.86	17.41	17.33	22.24	16.54
	GHGI	Mixed	56.06	51.59	50.41	49.24	45.72	45.75	47.73	45.48	47.60	51.02	57.50	49.83
Wearing a coat		Normal	37.96	42.79	46.52	45.95	45.72	47.39	47.82	39.89	40.14	41.35	36.29	42.89
		Bag	34.57	36.29	41.81	41.47	37.59	27.67	30.95	33.88	35.09	37.84	30.78	35.27
		Coat	98.97	99.83	98.79	99.14	98.79	98.62	98.28	97.76	95.69	96.72	98.28	98.26
	GEI	Mixed	57.16	59.64	62.38	62.18	60.70	57.89	59.01	57.17	56.97	58.64	55.11	58.81
		Normal	42.07	52.13	51.70	47.53	48.36	47.90	46.67	42.87	43.30	39.14	35.95	45.24
		Bag	41.90	44.91	45.17	45.95	47.76	41.47	39.57	42.24	44.14	40.43	40.00	43.05
		Coat	97.41	97.76	97.93	99.66	99.83	99.66	100.00	98.28	96.03	97.41	97.59	98.32
	GEnI	Mixed	60.46	64.93	64.93	64.38	65.32	63.01	62.08	61.13	61.16	58.99	57.84	62.20
		Normal	19.68	22.70	25.09	25.89	26.70	28.48	21.84	21.12	23.68	22.53	21.75	23.59
		Bag	15.60	15.52	16.38	16.12	13.19	10.17	12.33	14.57	15.95	15.95	16.64	14.76
		Coat	97.93	99.83	98.79	96.72	96.90	96.38	95.52	96.55	93.62	95.34	96.38	96.72
	GGI	Mixed	44.41	46.02	46.75	46.25	45.59	45.01	43.23	44.08	44.42	44.61	44.92	45.03
		Normal	26.15	24.66	26.64	27.16	28.25	28.22	24.28	23.59	26.90	21.64	31.12	26.24
		Bag	20.86	16.21	16.47	19.74	19.22	18.97	18.28	18.53	19.91	17.16	23.28	18.97
		Coat	97.93	98.62	98.79	99.83	97.24	96.21	95.86	96.38	93.79	94.48	96.21	96.85
	GHGI	Mixed	48.31	46.49	47.30	48.91	48.24	47.80	46.14	46.17	46.87	44.43	50.20	47.35
Normal walking and carrying a bag		Normal	96.34	95.31	93.41	93.34	93.34	89.90	91.69	89.66	90.41	93.66	94.72	92.89
		Bag	93.79	91.90	91.90	92.41	94.31	94.31	96.55	91.55	89.66	92.76	95.00	93.10
		Coat	52.67	59.22	58.97	61.21	65.09	64.57	62.41	55.69	52.41	53.28	49.66	57.74
	GEI	Mixed	80.94	82.14	81.43	82.32	84.25	82.93	83.55	78.97	77.49	79.90	79.79	81.25
		Normal	93.76	96.28	95.31	94.00	95.52	93.79	94.07	93.31	92.52	93.83	94.00	94.22
		Bag	92.76	94.66	92.76	92.76	94.14	96.38	97.07	94.83	92.76	95.52	94.31	94.36
		Coat	62.59	67.16	63.28	65.26	64.91	61.47	59.31	56.38	55.78	60.86	60.26	61.57
	GEnI	Mixed	83.03	86.03	83.78	84.01	84.86	83.88	83.48	81.51	80.35	83.40	82.86	83.38
		Normal	90.21	87.72	79.03	75.24	80.93	82.97	76.41	75.59	79.00	86.17	90.17	82.13
		Bag	86.03	84.48	79.14	77.41	78.10	84.83	75.86	74.66	74.66	83.28	85.17	80.33
		Coat	22.07	26.21	25.26	23.79	23.19	26.98	23.02	19.40	22.76	19.74	21.81	23.11
	GGI	Mixed	66.10	66.14	61.14	58.82	60.74	64.93	58.43	56.55	58.80	63.06	65.72	61.86
		Normal	92.14	89.97	82.97	82.07	82.83	86.10	82.66	83.14	84.10	86.52	91.38	85.81
		Bag	87.41	87.07	81.90	78.97	79.83	85.52	78.62	80.69	82.59	84.66	86.21	83.04
		Coat	33.45	27.33	28.10	28.28	25.95	29.40	25.95	25.17	24.74	23.36	33.97	27.79
	GHGI	Mixed	71.00	68.12	64.32	63.10	62.87	67.01	62.41	63.00	63.81	64.84	70.52	65.55
Normal		Normal	90.55	91.21	92.45	91.10	91.76	88.86	88.48	87.00	89.52	89.76	89.79	90.04
		Bag	71.21	70.34	68.79	64.14	69.31	63.36	66.72	65.95	64.22	66.90	69.57	67.32
	GEI	Coat	96.21	96.55	96.38	96.90	95.17	95.00	95.69	94.31	93.28	93.10	92.76	95.03

		Mixed	85.99	86.03	85.87	84.05	85.41	82.41	83.63	82.42	82.34	83.25	84.04	84.13
		Normal	87.14	91.86	91.38	90.79	91.52	90.59	91.24	88.28	90.07	90.55	89.48	90.26
		Bag	74.91	76.55	71.21	70.34	70.95	68.62	71.72	70.60	69.66	76.21	76.47	72.48
		Coat	96.03	95.69	93.97	95.17	94.66	94.66	95.17	93.45	93.79	94.83	95.17	94.78
	GEnI	Mixed	86.03	88.03	85.52	85.44	85.71	84.62	86.05	84.11	84.51	87.20	87.04	85.84
		Normal	68.79	70.45	66.72	72.41	73.24	69.86	65.66	69.52	68.00	69.55	75.21	69.95
		Bag	38.71	41.12	37.33	33.71	29.22	27.33	27.84	28.10	30.69	32.41	42.07	33.50
		Coat	75.52	76.38	72.59	74.48	78.45	74.66	73.10	71.03	69.83	70.17	75.69	73.81
	GGI	Mixed	61.01	62.65	58.88	60.20	60.30	57.28	55.53	56.22	56.17	57.38	64.32	59.09
		Normal	78.55	75.00	74.69	71.62	73.41	67.31	68.24	70.62	66.45	70.55	82.48	72.63
		Bag	50.60	46.21	39.83	39.40	39.22	36.98	32.24	38.28	36.29	41.47	55.00	41.41
		Coat	80.00	79.83	77.59	73.79	75.52	72.41	75.17	69.83	66.90	69.48	82.07	74.78
	GHGI	Mixed	69.72	67.01	64.03	61.60	62.72	58.90	58.55	59.57	56.55	60.50	73.18	62.94
Carrying a bag and wearing a coat		Normal	73.51	70.09	68.45	64.97	66.61	69.20	65.78	65.55	59.48	67.47	70.23	67.39
		Bag	85.52	84.14	85.52	86.72	90.00	88.10	88.97	86.38	85.00	84.48	82.07	86.08
		Coat	89.48	91.72	89.48	92.76	96.90	95.17	93.45	89.31	88.97	87.76	86.03	91.00
	GEI	Mixed	82.84	81.98	81.15	81.48	84.50	84.16	82.73	80.41	77.82	79.90	79.44	81.49
		Normal	74.37	77.76	72.30	69.43	70.20	69.57	70.20	71.72	70.03	73.65	69.31	71.68
		Bag	87.93	84.66	85.34	85.00	86.21	86.90	88.62	87.07	87.24	88.79	86.38	86.74
		Coat	91.90	93.79	90.86	92.07	90.17	92.24	91.21	90.34	89.31	91.38	91.72	91.36
	GEnI	Mixed	84.73	85.40	82.84	82.16	82.19	82.90	83.34	83.05	82.19	84.61	82.47	83.26
		Normal	45.09	45.89	37.27	34.91	37.47	41.44	36.38	32.53	37.21	41.06	46.29	39.60
		Bag	65.00	63.10	57.76	62.76	65.52	64.31	55.86	61.55	62.41	61.55	69.66	62.68
		Coat	67.24	66.72	63.79	66.90	74.48	70.17	63.45	65.69	60.69	65.69	71.03	66.90
	GGI	Mixed	59.11	58.57	52.94	54.86	59.16	58.64	51.90	53.26	53.44	56.10	62.33	56.39
		Normal	55.72	44.48	42.99	43.97	41.24	42.96	38.82	39.48	38.85	42.30	58.45	44.48
		Bag	72.76	69.31	65.34	63.79	71.72	60.69	56.55	64.14	62.59	61.55	75.86	65.85
		Coat	78.45	77.24	71.55	69.83	75.00	70.00	63.79	66.72	62.76	65.34	76.21	70.63
	GHGI	Mixed	68.98	63.68	59.96	59.20	62.65	57.88	53.06	56.78	54.73	56.40	70.17	60.32
Mixed three appearances		Normal	96.93	96.93	96.07	95.55	95.66	93.90	94.97	93.97	92.83	94.90	96.07	95.25
		Bag	95.69	92.93	93.45	93.62	95.17	96.03	98.45	96.72	95.34	95.17	94.83	95.22
		Coat	98.28	98.28	98.28	98.97	99.48	96.90	98.97	98.28	97.59	99.31	97.93	98.39
	GEI	Mixed	96.97	96.05	95.93	96.05	96.77	95.61	97.46	96.32	95.25	96.46	96.28	96.29
		Normal	94.24	96.41	96.28	96.00	95.66	95.17	94.86	93.76	93.76	93.72	92.66	94.77
		Bag	94.83	92.93	93.97	93.97	95.17	95.52	98.28	97.24	96.72	98.62	95.17	95.67
		Coat	98.10	98.97	97.24	98.79	98.10	98.10	97.59	97.41	97.93	96.03	99.31	97.96
	GEnI	Mixed	95.72	96.10	95.83	96.25	96.31	96.26	96.91	96.14	96.14	96.13	95.71	96.14
		Normal	92.03	89.38	81.34	80.86	87.34	85.45	82.34	83.38	83.52	89.72	93.72	86.28
		Bag	84.31	83.97	81.72	81.03	80.69	83.28	78.97	78.62	80.69	82.41	88.28	82.18
		Coat	92.07	93.62	84.14	86.90	88.28	86.21	84.66	81.03	82.07	86.38	90.00	86.85
	GGI	Mixed	89.47	88.99	82.40	82.93	85.44	84.98	81.99	81.01	82.09	86.17	90.67	85.10
		Normal	94.38	92.10	87.90	84.21	87.55	85.41	84.59	86.69	86.93	87.14	93.79	88.24
		Bag	86.03	87.24	85.00	80.17	84.14	83.10	82.07	83.97	84.31	82.93	89.31	84.39
		Coat	94.14	95.34	90.52	89.66	90.17	87.76	90.00	85.17	84.66	85.34	91.55	89.48
	GHGI	Mixed	91.52	91.56	87.80	84.68	87.29	85.43	85.55	85.28	85.30	85.14	91.55	87.37

Appendix B – Chapter 4 Additional Results

B.1 CCR of SVM and CNN feature by CNN architecture in Figure 4.5

	GEnI				GGI				GGEnI			
Layer	Normal	Bag	Coat	Average	Normal	Bag	Coat	Average	Normal	Bag	Coat	Average
11	98.08	58.86	38.17	65.05	97.73	34.60	15.44	49.26	97.18	38.05	20.26	51.83
10	98.63	69.12	45.10	70.91	98.16	41.07	19.24	52.82	98.16	47.73	27.12	57.67
9	99.02	79.74	54.35	77.66	98.82	51.45	24.96	58.41	98.55	60.82	33.74	64.37
8	99.06	81.86	56.43	79.10	98.98	53.72	26.10	59.60	98.79	64.15	33.19	65.37
7	98.98	81.03	55.21	78.42	98.71	51.61	24.65	58.32	98.67	61.99	32.99	64.55
6	99.06	83.74	59.09	80.66	98.86	55.84	27.82	60.84	98.75	65.91	35.27	66.64
5	99.18	84.95	59.68	81.24	98.94	56.90	28.17	61.34	98.90	66.38	33.42	66.24
4	98.98	82.17	56.82	79.38	98.59	53.92	26.65	59.72	98.75	63.75	33.54	65.35
3	99.06	84.05	59.40	80.84	98.75	56.86	28.02	61.21	98.82	65.67	33.66	66.05
2	99.10	84.60	59.87	81.17	98.79	56.97	28.02	61.26	98.82	65.52	33.66	66.00
1	99.10	82.37	59.05	80.19	99.10	54.90	27.55	60.51	98.98	65.01	35.11	66.37

B.2 CCR of CGI when training with four normal walking dataset

			View Angle											
			0	18	36	54	72	90	108	126	144	162	180	Average
Convolutional	GEI	Normal	99.57	100.00	99.57	98.71	98.71	99.14	99.14	99.14	98.36	98.79	99.14	99.11
		Bag	76.72	73.19	74.91	65.52	65.86	66.81	70.17	69.57	70.09	72.16	78.97	71.27
		Coat	48.28	58.36	55.60	60.43	57.33	59.22	57.67	54.57	53.10	51.98	50.86	55.22
		Mixed	74.86	77.18	76.70	74.89	73.97	75.06	75.66	74.43	73.85	74.31	76.32	75.20
	GEnI	Normal	99.14	99.57	99.57	99.40	99.48	98.97	98.71	99.14	98.71	98.79	99.14	99.15
		Bag	83.88	83.02	80.78	76.38	78.10	77.16	79.22	76.81	78.71	82.50	85.86	80.22
		Coat	59.74	63.88	61.72	64.22	59.74	53.88	54.05	58.10	59.66	60.78	55.86	59.24
		Mixed	80.92	82.16	80.69	80.00	79.11	76.67	77.33	78.02	79.02	80.69	80.29	79.54
	GGI	Normal	100.00	100.00	99.14	99.14	98.28	99.14	97.84	98.71	98.71	99.14	99.48	99.05
		Bag	61.55	61.98	50.86	45.52	34.14	34.40	34.66	40.09	45.00	53.28	60.69	47.47
		Coat	20.52	29.57	29.31	29.66	31.47	35.86	30.09	32.76	29.31	26.55	26.55	29.24
		Mixed	60.69	63.85	59.77	58.10	54.63	56.47	54.20	57.18	57.67	59.66	62.24	58.59
	GHGI	Normal	100.00	100.00	99.14	98.88	98.71	98.19	98.28	98.71	98.02	99.40	99.14	98.95
		Bag	68.97	65.69	58.88	53.10	51.64	55.95	51.55	51.03	52.16	56.81	70.95	57.88
		Coat	35.26	29.31	33.45	31.03	33.19	33.02	30.43	30.86	28.02	27.16	38.45	31.83
		Mixed	68.07	65.00	63.82	61.01	61.18	62.39	60.09	60.20	59.40	61.12	69.51	62.89
Convolutional and	GEI	Normal	99.74	100.00	99.66	99.05	99.05	99.14	99.14	99.05	98.79	99.40	99.48	99.32
		Bag	80.00	79.57	81.29	74.40	78.97	77.93	79.74	80.34	78.36	78.28	82.24	79.19
		Coat	50.26	62.16	61.81	68.53	69.57	69.91	69.83	62.50	62.16	57.93	53.53	62.56
		Mixed	76.67	80.57	80.92	80.66	82.53	82.33	82.90	80.63	79.77	78.53	78.42	80.36
	GEnI	Normal	99.57	99.83	99.57	99.48	99.22	98.71	98.71	98.97	98.88	99.05	99.05	99.18
		Bag	84.91	84.66	84.40	83.28	84.83	85.60	86.38	84.57	83.71	84.57	84.48	84.67
		Coat	60.52	66.72	69.48	73.02	67.59	64.40	64.14	62.84	65.95	64.57	58.02	65.20
		Mixed	81.67	83.74	84.48	85.26	83.88	82.90	83.07	82.13	82.84	82.73	80.52	83.02

	GGI	Normal	100.00	100.00	99.66	99.31	98.71	98.62	97.07	99.05	98.53	99.22	99.14	99.03
		Bag	64.31	63.36	55.78	51.38	43.02	44.14	43.62	49.14	50.86	56.98	65.95	53.50
		Coat	21.72	29.05	33.02	35.43	35.34	37.67	33.28	33.53	31.03	24.48	26.38	31.00
		Mixed	62.01	64.14	62.82	62.04	59.02	60.14	57.99	60.57	60.14	60.23	63.82	61.18
	GHGI	Normal	100.00	100.00	99.40	98.97	98.71	97.84	98.62	98.62	98.02	99.14	99.14	98.95
		Bag	67.76	65.78	62.50	57.16	59.14	62.76	56.90	56.90	56.47	56.90	69.66	61.08
		Coat	32.16	28.79	34.31	35.34	36.21	35.95	34.83	33.36	28.02	23.79	35.43	32.56
		Mixed	66.64	64.86	65.40	63.82	64.68	65.52	63.45	62.96	60.83	59.94	68.07	64.20
Average Convolutional and Normalization	GEI	Normal	99.74	100.00	99.66	98.97	98.97	99.22	99.22	99.31	99.14	99.40	99.57	99.38
		Bag	82.67	81.81	83.19	78.10	80.17	79.83	81.29	81.64	79.83	80.95	82.59	81.10
		Coat	53.19	63.36	65.09	70.60	72.50	72.24	71.38	66.64	63.97	59.48	56.21	64.97
		Mixed	78.53	81.72	82.64	82.56	83.88	83.76	83.97	82.53	80.98	79.94	79.45	81.82
	GEnI	Normal	99.40	99.74	99.66	99.48	99.31	98.88	98.79	99.14	98.88	98.79	99.14	99.20
		Bag	84.31	86.12	85.69	84.74	86.81	86.64	87.76	85.52	84.31	85.17	84.74	85.62
		Coat	61.21	70.26	72.24	75.52	71.12	67.93	65.95	66.81	68.45	65.26	59.83	67.69
		Mixed	81.64	85.37	85.86	86.58	85.75	84.48	84.17	83.82	83.88	83.07	81.24	84.17
	GGI	Normal	100.00	100.00	99.66	99.22	98.79	98.79	97.76	99.22	98.79	98.97	99.05	99.11
		Bag	66.29	66.64	59.14	56.47	50.60	53.36	51.21	53.10	54.40	60.52	66.72	58.04
		Coat	21.29	29.31	33.19	37.50	40.17	41.55	37.07	34.22	31.21	24.57	25.52	32.33
		Mixed	62.53	65.32	63.99	64.40	63.19	64.57	62.01	62.18	61.47	61.35	63.76	63.16
	GHGI	Normal	100.00	100.00	99.48	99.14	98.71	98.19	98.97	98.79	98.19	98.97	99.14	99.05
		Bag	68.71	66.98	63.97	61.29	61.81	66.12	61.55	59.57	57.41	56.55	68.53	62.95
		Coat	28.88	27.41	35.34	38.88	39.40	40.00	35.69	34.05	27.84	23.88	33.02	33.13
		Mixed	65.86	64.80	66.26	66.44	66.64	68.10	65.40	64.14	61.15	59.80	66.90	65.04

B.3 CCR of GHGI when training with different number of normal walking datasets

			View Angle											
			0	18	36	54	72	90	108	126	144	162	180	Average
1	GEI	Normal	90.09	93.79	96.81	97.89	97.67	96.08	95.82	95.82	94.35	94.74	94.61	95.24
		Bag	80.39	83.19	82.54	81.36	86.10	85.56	88.04	84.91	81.57	84.27	84.16	83.83
		Coat	82.54	82.54	79.42	76.51	82.54	79.31	75.75	76.40	74.68	74.89	75.11	78.15
		Mixed	84.34	86.51	86.26	85.25	88.77	86.98	86.54	85.71	83.53	84.63	84.63	85.74
	GEnI	Normal	88.19	93.49	95.69	97.20	97.11	95.99	95.56	95.47	93.36	93.45	92.16	94.33
		Bag	78.88	81.25	80.82	79.74	84.27	84.91	85.99	80.50	81.25	81.68	80.28	81.78
		Coat	80.17	81.36	77.16	78.02	81.68	77.59	74.25	73.06	72.84	72.41	72.52	76.46
		Mixed	82.41	85.37	84.55	84.99	87.69	86.16	85.27	83.01	82.49	82.51	81.65	84.19
	GGI	Normal	98.28	98.02	95.82	93.88	95.99	94.09	94.09	96.08	96.59	97.54	98.62	96.27
		Bag	76.72	71.34	62.82	57.22	59.81	68.43	66.81	70.58	66.59	68.10	77.16	67.78
		Coat	40.73	44.94	45.15	44.83	48.28	45.26	40.73	36.75	37.39	35.88	39.12	41.73
		Mixed	71.91	71.43	67.93	65.31	68.02	69.26	67.21	67.80	66.86	67.18	71.63	68.60
	GHGI	Normal	97.37	96.16	93.92	94.05	95.30	93.75	94.57	95.65	95.04	96.90	97.41	95.47
		Bag	74.35	66.59	61.96	59.38	63.15	70.91	68.32	68.53	64.12	64.98	72.74	66.82
		Coat	36.96	39.44	45.15	44.83	43.00	40.73	35.45	33.08	36.53	35.56	37.93	38.97
		Mixed	69.56	67.40	67.01	66.08	67.15	68.46	66.11	65.75	65.23	65.81	69.36	67.09
2	GEI	Normal	95.96	98.11	98.28	98.81	98.87	98.71	98.65	98.76	98.11	98.60	96.39	98.11
		Bag	87.72	90.63	89.66	93.43	95.04	94.94	93.43	92.89	87.50	88.25	86.21	90.88
		Coat	86.85	93.43	91.49	91.92	89.22	86.31	82.44	82.76	86.21	84.70	83.73	87.19

		Mixed	90.18	94.06	93.14	94.72	94.38	93.32	91.51	91.47	90.61	90.52	88.78	92.06
		Normal	95.31	96.93	98.28	98.92	98.71	98.92	98.28	98.60	97.79	97.63	95.20	97.69
		Bag	86.64	88.36	89.76	93.00	94.29	95.15	94.40	91.92	88.79	87.18	85.78	90.48
		Coat	86.53	91.70	90.09	91.92	87.61	85.45	82.97	82.97	84.70	82.11	80.82	86.08
	GEnI	Mixed	89.49	92.33	92.71	94.61	93.53	93.18	91.88	91.16	90.43	88.97	87.27	91.42
		Normal	99.52	99.73	99.46	99.62	99.30	98.76	98.81	98.60	98.60	99.78	99.84	99.28
		Bag	82.65	78.23	70.37	75.97	88.69	89.44	88.58	85.88	82.87	77.69	83.08	82.13
		Coat	55.28	55.39	62.39	68.43	68.43	66.27	56.68	56.25	58.30	48.81	52.26	58.95
	GGI	Mixed	79.15	77.78	77.41	81.34	85.47	84.82	81.36	80.24	79.92	75.43	78.39	80.12
		Normal	99.14	99.35	98.87	99.03	99.25	98.71	98.76	98.33	98.38	99.78	99.41	99.00
		Bag	83.73	75.86	69.50	75.54	87.28	89.98	87.07	83.84	82.44	76.40	82.11	81.25
		Coat	56.57	54.85	66.49	67.03	68.64	64.87	52.91	55.60	54.42	49.57	53.66	58.60
	GHGI	Mixed	79.81	76.69	78.29	80.53	85.06	84.52	79.58	79.26	78.41	75.25	78.39	79.62
		Normal	96.62	97.84	98.20	98.20	98.20	98.28	98.85	98.56	97.70	97.99	96.05	97.86
		Bag	88.79	92.03	91.06	92.03	95.69	95.91	94.29	93.00	87.93	88.04	85.67	91.31
		Coat	86.85	92.35	90.63	90.84	89.55	86.42	83.73	84.59	84.27	84.05	83.84	87.01
	GEI	Mixed	90.76	94.07	93.30	93.69	94.48	93.53	92.29	92.05	89.97	90.03	88.52	92.06
		Normal	96.26	97.63	98.35	99.28	98.85	98.99	98.85	98.85	97.70	97.99	96.19	98.09
		Bag	88.69	89.66	91.06	93.21	96.23	95.69	94.83	92.78	87.50	85.45	84.05	90.83
		Coat	86.75	90.95	90.19	91.49	86.96	85.13	83.41	83.51	84.38	83.84	82.11	86.25
3	GEnI	Mixed	90.57	92.74	93.20	94.66	94.01	93.27	92.36	91.71	89.86	89.09	87.45	91.72
		Normal	100.00	100.00	99.71	100.00	99.43	98.85	99.35	99.21	99.43	99.93	100.00	99.63
		Bag	86.85	80.39	77.80	83.19	90.30	92.24	87.72	85.56	83.41	78.66	85.99	84.74
		Coat	54.63	60.34	67.03	72.74	71.44	69.29	61.64	56.03	60.99	51.72	56.03	61.99
	GGI	Mixed	80.50	80.24	81.51	85.31	87.06	86.79	82.90	80.27	81.27	76.77	80.68	82.12
		Normal	100.00	100.00	99.43	100.00	99.28	98.92	98.92	99.57	99.28	99.64	100.00	99.55
		Bag	84.70	79.63	76.62	82.22	88.15	91.49	88.47	83.30	83.94	76.40	84.70	83.60
		Coat	58.62	58.73	67.35	70.69	71.12	67.67	61.21	56.79	59.81	54.20	55.82	62.00
	GHGI	Mixed	81.11	79.45	81.13	84.30	86.18	86.03	82.87	79.89	81.01	76.75	80.17	81.72
		Normal	96.12	99.57	99.14	99.46	99.14	98.71	98.71	98.81	98.71	99.57	96.98	98.63
		Bag	89.22	92.67	91.92	93.10	96.12	95.69	95.69	93.21	90.63	90.41	86.64	92.30
		Coat	87.28	91.49	92.89	91.27	89.76	89.01	86.21	86.96	86.42	86.75	84.91	88.45
	GEI	Mixed	90.88	94.58	94.65	94.61	95.01	94.47	93.53	93.00	91.92	92.24	89.51	93.13
		Normal	96.12	99.14	99.57	99.89	99.14	99.14	98.71	99.14	99.14	99.57	97.95	98.86
		Bag	89.33	91.70	91.81	94.94	96.55	95.69	96.12	92.56	90.84	87.93	86.21	92.15
		Coat	87.72	91.81	89.76	91.81	89.12	87.50	86.21	86.64	86.31	85.67	83.08	87.78
3	GEnI	Mixed	91.06	94.22	93.71	95.55	94.94	94.11	93.68	92.78	92.10	91.06	89.08	92.93
		Normal	100.00	100.00	99.57	100.00	99.57	98.71	99.14	100.00	100.00	100.00	100.00	99.73
		Bag	89.01	82.76	84.05	86.85	92.24	94.40	91.59	84.81	84.05	84.59	86.96	87.39
		Coat	56.03	63.79	69.83	73.71	72.84	70.91	65.19	62.18	63.36	57.87	56.90	64.78
	GGI	Mixed	81.68	82.18	84.48	86.85	88.22	88.00	85.31	82.33	82.47	80.82	81.29	83.97
		Normal	100.00	100.00	99.57	100.00	99.57	98.71	99.14	100.00	100.00	100.00	100.00	99.73
		Bag	86.21	81.25	81.90	85.99	88.25	93.86	90.95	85.13	83.94	80.71	84.16	85.67
		Coat	59.27	61.42	74.03	72.84	72.41	70.58	65.09	60.13	63.25	58.08	59.27	65.13
	GHGI	Mixed	81.82	80.89	85.17	86.28	86.75	87.72	85.06	81.75	82.40	79.60	81.14	83.51

B.4 CCR of CGHGI when training with four normal walking dataset (HOG-Histogram of Ortientated Gradients, Conv-Convolutional, Norm-Normalization)

			View Angle											
			0	18	36	54	72	90	108	126	144	162	180	Average
HOG+Conv+Norm		Normal	96.55	99.14	99.14	99.57	99.14	98.71	98.71	98.71	98.71	99.14	96.98	98.59
		Bag	89.22	91.81	91.81	92.67	96.12	95.69	95.26	93.10	90.09	90.52	86.64	92.08
		Coat	88.36	90.52	93.10	90.95	90.52	88.79	86.64	86.21	86.64	86.21	84.05	88.36
	GEI	Mixed	91.38	93.82	94.68	94.40	95.26	94.40	93.53	92.67	91.81	91.95	89.22	93.01
		Normal	96.12	99.14	99.57	100.00	99.14	99.14	98.71	99.14	98.71	99.14	98.28	98.82
		Bag	88.79	91.81	91.81	95.26	96.12	95.69	97.41	92.24	90.52	87.93	86.64	92.20
		Coat	85.78	90.95	89.66	90.52	88.36	86.64	86.64	86.64	85.34	84.91	83.62	87.19
	GEnI	Mixed	90.23	93.97	93.68	95.26	94.54	93.82	94.25	92.67	91.52	90.66	89.51	92.74
		Normal	100.00	100.00	99.57	100.00	99.57	98.71	99.14	99.57	100.00	100.00	100.00	99.69
		Bag	88.79	79.31	83.62	87.50	90.95	93.53	91.38	84.05	83.62	82.33	86.21	86.48
		Coat	55.60	61.21	68.10	71.98	71.55	68.53	63.36	61.64	63.36	56.47	56.90	63.52
	GGI	Mixed	81.47	80.17	83.76	86.49	87.36	86.93	84.63	81.75	82.33	79.60	81.03	83.23
		Normal	100.00	100.00	99.57	100.00	99.57	98.71	99.14	100.00	100.00	100.00	100.00	99.73
		Bag	84.48	78.88	81.47	86.64	89.22	93.10	90.52	84.05	83.19	80.60	84.48	85.15
		Coat	58.19	60.34	71.55	71.55	70.69	68.10	63.79	59.05	63.79	55.17	56.90	63.56
	GHGI	Mixed	80.89	79.74	84.20	86.06	86.49	86.64	84.48	81.03	82.33	78.59	80.46	82.81
HOG+Conv+Norm+Averge		Normal	96.55	99.14	99.57	99.14	98.71	98.71	98.71	98.28	98.71	99.57	96.98	98.55
		Bag	87.93	88.79	92.24	92.24	96.12	95.69	96.12	93.10	90.52	87.93	87.50	91.65
		Coat	86.21	92.67	90.95	90.95	88.79	86.64	85.78	83.19	85.34	85.34	86.21	87.46
	GEI	Mixed	90.23	93.53	94.25	94.11	94.54	93.68	93.53	91.52	91.52	90.95	90.23	92.55
		Normal	95.69	98.71	99.57	99.14	98.71	98.71	98.71	99.14	99.14	99.57	97.84	98.63
		Bag	87.07	88.79	91.81	93.10	95.69	94.83	94.83	93.97	90.09	86.64	86.64	91.22
		Coat	85.34	90.09	89.22	89.66	87.93	86.21	87.07	84.91	85.34	84.05	81.90	86.52
	GEnI	Mixed	89.37	92.53	93.53	93.97	94.11	93.25	93.53	92.67	91.52	90.09	88.79	92.12
		Normal	100.00	100.00	99.14	100.00	99.14	98.71	98.71	99.57	99.57	100.00	100.00	99.53
		Bag	86.64	78.88	75.86	81.47	89.22	90.52	90.52	82.76	76.72	77.59	87.07	83.39
		Coat	56.47	64.22	70.26	68.97	67.24	65.52	59.91	56.47	62.50	54.74	55.17	61.95
	GGI	Mixed	81.03	81.03	81.75	83.48	85.20	84.91	83.05	79.60	79.60	77.44	80.75	81.62
		Normal	100.00	100.00	99.57	100.00	99.14	98.71	98.71	99.57	99.14	99.57	100.00	99.49
		Bag	83.62	77.16	72.41	78.02	87.93	91.38	87.50	80.17	77.16	76.29	84.48	81.47
		Coat	60.34	64.66	68.53	74.14	66.38	63.79	60.34	59.91	62.50	55.17	53.02	62.62
	GHGI	Mixed	81.32	80.60	80.17	84.05	84.48	84.63	82.18	79.89	79.60	77.01	79.17	81.19
Conv+Norm+Average+HOG		Normal	96.55	99.14	99.14	99.57	99.14	98.71	98.71	99.14	98.71	99.57	96.98	98.67
		Bag	88.36	92.24	91.38	93.10	96.55	95.26	95.69	92.67	88.36	89.22	86.21	91.73
		Coat	87.50	91.38	91.38	90.52	91.38	88.79	87.07	87.07	86.64	87.07	84.91	88.52
	GEI	Mixed	90.80	94.25	93.97	94.40	95.69	94.25	93.82	92.96	91.24	91.95	89.37	92.97
		Normal	96.12	99.14	99.14	100.00	99.14	99.14	98.71	99.14	99.14	99.57	98.28	98.86
		Bag	88.36	91.81	91.38	94.40	96.55	95.26	95.69	92.67	88.79	88.79	85.78	91.77
		Coat	87.50	91.38	89.22	91.38	90.09	86.21	88.36	87.50	86.21	85.34	83.19	87.85
	GEnI	Mixed	90.66	94.11	93.25	95.26	95.26	93.53	94.25	93.10	91.38	91.24	89.08	92.83
		Normal	100.00	100.00	99.57	100.00	99.57	98.71	99.57	99.57	100.00	100.00	100.00	99.73
	GGI	Bag	88.36	80.60	82.33	84.48	89.66	93.10	90.52	81.03	81.03	84.05	87.50	85.70

		Coat	54.74	62.07	68.53	71.55	71.12	69.83	64.22	60.34	62.93	56.03	57.33	63.52
		Mixed	81.03	80.89	83.48	85.34	86.78	87.21	84.77	80.32	81.32	80.03	81.61	82.98
		Normal	100.00	100.00	99.57	100.00	99.57	98.71	99.14	100.00	100.00	100.00	100.00	99.73
		Bag	87.93	79.74	81.47	84.91	87.07	93.53	90.52	83.19	82.33	81.90	85.34	85.27
		Coat	58.19	59.05	71.98	72.41	68.97	69.40	65.52	59.05	61.21	57.33	59.48	63.87
	GHGI	Mixed	82.04	79.60	84.34	85.78	85.20	87.21	85.06	80.75	81.18	79.74	81.61	82.95

Appendix C – Chapter 5 Additional Results

C.1 GHGI MRD 1:4

Fusion	Appearance	View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Avg
1	Normal	96.98	98.71	99.14	98.28	98.28	98.28	98.71	98.28	96.98	97.84	96.98	98.04
	Bag	86.21	90.09	92.67	93.97	97.41	95.69	96.12	94.40	89.22	91.38	87.50	92.24
	Coat	87.93	89.22	88.79	87.07	89.22	88.36	84.48	83.62	85.34	84.05	84.48	86.60
	Mixed	90.37	92.67	93.53	93.10	94.97	94.11	93.10	92.10	90.52	91.09	89.66	92.29
2	Normal	96.12	98.71	99.14	98.71	98.28	98.28	98.28	97.41	96.55	96.98	96.98	97.77
	Bag	87.07	87.93	90.52	93.53	95.69	95.69	96.12	93.10	90.95	92.24	88.79	91.97
	Coat	84.05	83.62	83.19	84.05	83.62	80.17	79.74	80.17	81.03	80.60	75.43	81.43
	Mixed	89.08	90.09	90.95	92.10	92.53	91.38	91.38	90.23	89.51	89.94	87.07	90.39
3	Normal	96.12	98.28	98.71	99.14	99.14	98.71	98.71	98.28	97.84	99.14	97.84	98.35
	Bag	82.76	85.78	89.66	90.09	93.10	92.24	93.97	89.66	86.64	85.78	81.90	88.32
	Coat	88.36	91.81	89.66	87.50	87.93	85.34	84.05	79.74	84.05	83.62	83.19	85.93
	Mixed	89.08	91.95	92.67	92.24	93.39	92.10	92.24	89.22	89.51	89.51	87.64	90.87
4	Normal	96.12	97.84	98.71	99.14	98.71	98.71	98.28	98.28	97.84	98.71	96.98	98.12
	Bag	81.03	84.48	88.79	89.66	93.53	93.53	93.97	89.22	86.64	85.34	83.19	88.13
	Coat	89.22	90.95	89.66	87.93	87.07	86.21	84.48	81.47	83.62	83.62	84.05	86.21
	Mixed	88.79	91.09	92.39	92.24	93.10	92.82	92.24	89.66	89.37	89.22	88.07	90.82
5	Normal	96.12	99.14	98.28	99.14	98.28	98.71	98.28	98.28	96.98	97.84	97.41	98.04
	Bag	82.33	85.34	88.79	90.09	96.55	96.12	95.26	90.52	86.21	85.34	85.78	89.30
	Coat	90.52	90.52	91.38	87.50	87.93	87.07	84.48	82.33	84.48	85.78	86.21	87.11
	Mixed	89.66	91.67	92.82	92.24	94.25	93.97	92.67	90.37	89.22	89.66	89.80	91.48
6	Normal	95.69	99.14	98.28	99.57	98.28	97.84	98.71	98.28	97.41	97.84	96.98	98.00
	Bag	82.76	85.78	87.93	88.36	95.69	95.69	93.97	90.09	85.78	84.05	84.48	88.60
	Coat	88.79	89.22	90.52	86.21	87.50	85.78	82.76	80.60	84.05	84.48	86.21	86.01
	Mixed	89.08	91.38	92.24	91.38	93.82	93.10	91.81	89.66	89.08	88.79	89.22	90.87
7	Normal	95.69	98.28	98.71	99.14	99.14	98.71	98.28	97.84	97.84	99.14	97.84	98.24
	Bag	80.60	83.19	86.21	87.93	92.24	90.52	92.67	87.07	85.78	82.76	81.90	86.44
	Coat	87.50	91.81	90.09	87.93	87.50	84.91	84.05	82.33	84.48	83.19	84.05	86.17
	Mixed	87.93	91.09	91.67	91.67	92.96	91.38	91.67	89.08	89.37	88.36	87.93	90.28
8	Normal	94.83	97.41	97.84	99.14	98.71	99.14	97.84	97.41	97.84	98.71	96.98	97.81
	Bag	79.74	81.03	84.91	87.50	92.24	91.38	91.81	87.07	84.05	80.17	80.17	85.46
	Coat	89.66	90.52	89.66	88.36	87.50	86.64	84.48	81.03	83.19	83.62	86.64	86.48
	Mixed	88.07	89.66	90.80	91.67	92.82	92.39	91.38	88.51	88.36	87.50	87.93	89.92
9	Normal	93.97	97.41	97.84	98.28	98.71	97.41	96.55	96.55	96.98	95.26	95.69	96.79
	Bag	78.02	79.74	80.17	86.21	93.97	93.10	90.95	84.91	82.76	75.86	81.47	84.29
	Coat	90.09	89.66	92.24	86.21	87.50	86.21	85.34	82.76	82.33	81.90	86.64	86.44
	Mixed	87.36	88.94	90.09	90.23	93.39	92.24	90.95	88.07	87.36	84.34	87.93	89.17
10	Normal	93.97	97.41	97.41	98.28	97.84	96.98	96.98	96.55	96.55	95.26	95.69	96.63
	Bag	78.88	76.29	78.02	83.62	91.38	91.38	86.64	84.48	80.60	76.72	79.31	82.48
	Coat	86.21	89.66	88.79	85.78	85.78	84.05	82.33	81.90	83.62	80.17	86.64	84.99
	Mixed	86.35	87.79	88.07	89.22	91.67	90.80	88.65	87.64	86.93	84.05	87.21	88.04
11	Normal	96.12	98.71	98.71	99.14	99.14	98.71	98.28	98.28	97.84	99.14	97.84	98.35

	Bag	82.33	84.48	89.22	90.09	93.10	94.40	94.40	89.66	86.21	85.78	82.76	88.40
	Coat	87.50	91.81	88.79	88.36	86.64	85.78	84.91	81.90	85.34	84.48	84.91	86.40
	Mixed	88.65	91.67	92.24	92.53	92.96	92.96	92.53	89.94	89.80	89.80	88.51	91.05
	Normal	96.12	97.84	98.28	99.14	98.71	98.28	98.28	97.84	97.84	98.28	96.98	97.96
	Bag	80.60	84.48	86.64	89.22	93.10	93.10	93.97	90.09	86.64	85.34	83.19	87.85
	Coat	88.79	90.52	90.09	88.36	87.07	86.64	85.34	82.76	84.05	84.05	86.21	86.72
12	Mixed	88.51	90.95	91.67	92.24	92.96	92.67	92.53	90.23	89.51	89.22	88.79	90.84
	Normal	95.26	97.84	98.28	98.71	98.71	97.41	96.98	97.84	96.98	96.98	96.55	97.41
	Bag	81.47	83.19	87.93	90.09	96.12	96.12	96.12	88.36	86.21	82.33	84.48	88.40
	Coat	89.66	88.79	91.81	88.36	87.50	87.07	84.91	81.03	83.62	82.76	86.21	86.52
13	Mixed	88.79	89.94	92.67	92.39	94.11	93.53	92.67	89.08	88.94	87.36	89.08	90.78
	Normal	94.83	97.84	98.71	98.28	97.41	98.28	97.41	98.28	96.98	97.41	96.55	97.45
	Bag	82.33	81.47	84.48	86.64	94.40	93.97	92.24	88.36	85.34	82.33	82.76	86.76
	Coat	88.36	87.07	89.66	86.64	87.07	84.91	84.05	81.03	84.91	81.47	86.21	85.58
14	Mixed	88.51	88.79	90.95	90.52	92.96	92.39	91.24	89.22	89.08	87.07	88.51	89.93

C.6 GHGI and View Angle Classification with single parts

			View Angle										
				1	3	5	7	9	10	12	14	16	18	Average
1		Normal	98.7	99.1	98.7	99.1	100.0	95.6	97.8	99.5	99.1	99.5	99.5	98.8
		Bag	94.4	93.9	92.6	96.1	94.4	92.6	94.4	96.9	92.6	93.9	95.2	94.3
		Coat	95.6	96.1	94.4	94.4	94.4	92.6	94.4	96.1	96.1	92.6	88.7	94.1
	GEI	Mixed	96.2	96.4	95.2	96.5	96.2	93.6	95.5	97.5	95.9	95.4	94.5	95.7
		Normal	98.7	100.0	98.7	99.5	100.0	96.5	98.7	99.1	99.1	99.5	99.1	99.0
		Bag	95.2	93.1	93.1	96.9	94.4	92.6	94.8	97.4	93.9	93.1	93.5	94.4
		Coat	96.9	97.4	93.9	93.9	93.1	92.6	94.8	96.9	95.2	91.8	87.9	94.0
	GEnI	Mixed	96.9	96.8	95.2	96.8	95.8	93.9	96.1	97.8	96.1	94.8	93.5	95.8
		Normal	100.0	100.0	100.0	100.0	100.0	98.7	99.5	100.0	100.0	100.0	100.0	99.8
		Bag	100.0	99.5	98.7	98.2	95.6	96.9	93.1	98.2	96.1	95.2	96.1	97.1
		Coat	97.4	98.7	98.2	97.8	96.1	94.8	98.7	98.2	96.1	94.8	93.9	96.8
	GGI	Mixed	99.1	99.4	98.9	98.7	97.2	96.8	97.1	98.8	97.4	96.7	96.7	97.9
		Normal	99.5	100.0	100.0	100.0	100.0	99.1	99.1	100.0	100.0	100.0	100.0	99.8
		Bag	98.7	99.5	98.2	98.7	94.8	97.4	94.4	98.2	95.2	95.2	97.4	97.1
		Coat	96.9	97.8	98.2	97.4	96.1	93.5	97.8	98.7	96.1	94.8	94.4	96.5
	GHGI	Mixed	98.4	99.1	98.8	98.7	96.9	96.7	97.1	98.9	97.1	96.7	97.2	97.8
2		Normal	90.0	78.0	75.0	75.8	69.4	67.2	49.1	59.0	73.7	70.6	76.2	71.3
		Bag	81.4	56.4	40.9	59.4	37.0	66.3	26.7	25.8	54.7	50.4	56.4	50.5
		Coat	76.2	61.6	49.5	56.4	51.7	52.5	30.6	38.7	57.7	50.0	54.3	52.7
	GEI	Mixed	82.6	65.3	55.1	63.9	52.7	62.0	35.4	41.2	62.0	57.0	62.3	58.1
		Normal	90.0	74.5	72.8	74.5	70.2	65.5	45.6	61.6	74.1	71.5	76.2	70.6
		Bag	81.9	55.6	42.6	59.0	39.6	65.9	29.7	19.4	52.1	49.5	56.4	50.2
		Coat	78.0	60.7	51.7	52.1	53.8	53.4	26.7	32.7	55.6	50.4	53.8	51.7
	GEnI	Mixed	83.3	63.6	55.7	61.9	54.6	61.6	34.0	37.9	60.6	57.1	62.2	57.5
		Normal	90.9	79.7	78.8	80.6	78.0	71.9	63.7	75.0	76.2	74.5	77.5	77.0
		Bag	77.1	58.6	36.2	68.9	43.9	74.1	50.4	43.1	63.3	60.3	58.1	57.6
	GGI	Coat	78.4	64.2	53.8	61.6	59.4	66.8	60.3	58.6	68.5	59.4	67.6	63.5

		Mixed	82.18	67.53	56.32	70.40	60.49	70.98	58.19	58.91	69.40	64.80	67.82	66.09
		Normal	90.95	80.60	75.43	77.59	75.86	72.84	67.24	73.28	76.72	74.57	75.00	76.37
		Bag	78.88	58.62	40.95	71.98	45.69	71.55	53.88	42.24	64.66	62.50	58.62	59.05
		Coat	77.59	63.36	53.45	60.78	62.50	60.34	62.50	54.31	67.24	60.78	65.95	62.62
	GHGI	Mixed	82.47	67.53	56.61	70.11	61.35	68.25	61.21	56.61	69.54	65.95	66.52	66.01
		Normal	90.52	79.74	84.05	82.33	78.02	75.43	72.84	85.34	82.33	81.47	82.76	81.35
		Bag	65.52	55.60	54.31	66.38	51.29	67.67	49.57	40.09	67.24	53.88	51.72	56.66
		Coat	54.31	54.31	44.40	29.74	61.21	20.69	20.69	20.26	38.36	30.60	42.67	37.93
	GEI	Mixed	70.11	63.22	60.92	59.48	63.51	54.60	47.70	48.56	62.64	55.32	59.05	58.65
		Normal	89.66	78.02	83.19	80.60	80.60	75.43	71.55	84.05	86.21	82.33	79.31	81.00
		Bag	67.24	58.62	50.43	67.24	50.43	67.67	50.86	37.50	67.24	59.05	51.29	57.05
		Coat	58.19	52.16	37.07	30.60	54.31	14.66	18.10	20.69	35.78	28.02	44.83	35.85
3	GEnI	Mixed	71.70	62.93	56.90	59.48	61.78	52.59	46.84	47.41	63.07	56.47	58.48	57.97
		Normal	88.36	85.34	88.36	94.83	93.97	89.22	84.91	87.07	84.91	88.36	83.19	88.05
		Bag	61.64	66.38	69.40	87.07	78.45	84.91	76.72	64.66	76.72	64.22	59.05	71.75
		Coat	23.71	67.67	48.71	46.98	60.78	30.17	34.48	33.19	50.00	43.97	83.62	47.57
	GGI	Mixed	57.90	73.13	68.82	76.29	77.73	68.10	65.37	61.64	70.55	65.52	75.29	69.12
		Normal	85.78	87.93	89.22	95.26	92.24	87.93	85.34	85.78	86.21	88.79	84.48	88.09
		Bag	58.62	71.98	70.69	87.50	78.02	82.76	77.16	59.91	79.31	65.09	62.07	72.10
		Coat	21.98	68.53	47.41	42.67	60.34	30.17	29.74	29.31	46.98	44.83	86.64	46.24
	GHGI	Mixed	55.46	76.15	69.11	75.14	76.87	66.95	64.08	58.33	70.83	66.24	77.73	68.81
		Normal	94.83	91.81	88.79	89.22	87.50	78.88	74.57	84.05	87.07	85.78	87.50	86.36
		Bag	78.88	66.81	58.19	76.29	54.31	72.84	50.00	44.40	69.40	60.78	66.81	63.52
		Coat	75.00	69.83	53.02	45.69	60.34	31.47	25.86	27.16	54.31	41.81	56.90	49.22
	GEI	Mixed	82.90	76.15	66.67	70.40	67.39	61.06	50.14	51.87	70.26	62.79	70.40	66.37
		Normal	93.97	91.81	88.36	87.07	84.48	81.90	73.71	81.90	86.64	86.64	85.78	85.66
		Bag	82.76	66.81	57.33	75.43	54.31	70.69	49.57	45.26	67.67	60.78	64.66	63.21
		Coat	74.57	68.97	50.43	47.41	61.21	27.16	21.12	24.57	52.16	37.93	59.05	47.69
4	GEnI	Mixed	83.76	75.86	65.37	69.97	66.67	59.91	48.13	50.57	68.82	61.78	69.83	65.52
		Normal	96.12	98.71	96.55	96.55	99.14	93.53	92.67	95.69	92.24	96.12	94.83	95.65
		Bag	85.78	82.33	74.14	91.81	85.34	87.93	78.45	76.29	83.19	76.29	70.69	81.11
		Coat	71.98	82.33	58.62	53.88	65.95	36.64	47.41	49.14	65.95	50.00	85.78	60.70
	GGI	Mixed	84.63	87.79	76.44	80.75	83.48	72.70	72.84	73.71	80.46	74.14	83.76	79.15
		Normal	97.41	98.28	95.26	95.69	96.98	94.40	93.10	95.26	92.24	95.26	93.53	95.22
		Bag	84.05	82.33	73.71	90.95	83.62	87.07	81.03	71.98	84.48	76.72	73.28	80.84
		Coat	71.55	80.60	56.90	54.74	68.97	34.48	44.40	45.69	65.09	49.14	87.07	59.87
	GHGI	Mixed	84.34	87.07	75.29	80.46	83.19	71.98	72.84	70.98	80.60	73.71	84.63	78.64
		Normal	93.10	94.83	89.66	91.81	90.09	84.91	81.03	89.66	89.66	89.66	90.95	89.58
		Bag	75.00	62.93	54.31	65.52	56.90	53.88	60.78	36.21	56.90	48.71	65.09	57.84
		Coat	54.74	62.07	53.02	26.72	54.74	38.36	35.78	25.86	37.93	49.14	50.00	44.40
	GEI	Mixed	74.28	73.28	65.66	61.35	67.24	59.05	59.20	50.57	61.49	62.50	68.68	63.94
5		Normal	92.67	95.26	90.09	92.67	91.38	86.21	83.62	90.09	87.50	87.93	87.50	89.54
		Bag	76.72	61.21	54.74	61.64	58.19	49.57	58.19	38.36	59.05	46.98	62.07	56.97
		Coat	58.19	62.50	47.84	27.16	46.55	34.48	25.86	24.14	33.62	40.52	52.59	41.22
	GEnI	Mixed	75.86	72.99	64.22	60.49	65.37	56.75	55.89	50.86	60.06	58.48	67.39	62.58
		Normal	94.40	98.71	100.00	97.41	97.84	97.41	95.26	99.14	96.12	97.84	94.40	97.14
	GGI	Bag	69.83	80.17	73.71	84.91	87.07	79.31	76.29	65.09	81.47	69.40	81.03	77.12

		Coat	29.31	67.24	39.22	48.28	63.79	46.12	48.71	42.67	43.97	47.84	91.38	51.68
		Mixed	64.51	82.04	70.98	76.87	82.90	74.28	73.42	68.97	73.85	71.70	88.94	75.31
		Normal	93.97	98.71	99.14	98.28	98.28	96.98	94.40	97.41	95.69	96.98	93.10	96.63
		Bag	70.69	83.19	75.86	84.48	83.62	79.74	70.26	64.66	80.60	70.26	82.33	76.88
		Coat	28.02	65.09	42.67	45.26	61.21	39.66	48.28	37.07	44.83	50.43	91.81	50.39
	GHGI	Mixed	64.22	82.33	72.56	76.01	81.03	72.13	70.98	66.38	73.71	72.56	89.08	74.63
6		Normal	96.12	93.97	92.24	92.24	92.67	87.50	81.03	90.52	92.67	90.52	91.38	90.99
		Bag	79.31	65.95	56.03	57.33	56.90	49.57	62.07	42.24	61.64	47.41	61.64	58.19
		Coat	60.78	68.53	50.00	21.55	44.83	44.40	44.83	27.16	38.79	44.40	48.28	44.87
	GEI	Mixed	78.74	76.15	66.09	57.04	64.80	60.49	62.64	53.30	64.37	60.78	67.10	64.68
		Normal	93.53	95.26	93.10	92.67	92.67	86.64	82.33	90.95	90.09	88.79	88.79	90.44
		Bag	79.74	62.50	54.31	56.47	58.62	41.81	62.07	38.79	59.48	49.14	62.07	56.82
		Coat	64.66	63.36	46.12	25.43	38.79	42.24	33.19	25.00	32.76	34.91	47.84	41.30
	GEnI	Mixed	79.31	73.71	64.51	58.19	63.36	56.90	59.20	51.58	60.78	57.61	66.24	62.85
		Normal	94.83	99.57	100.00	98.71	98.71	96.98	96.12	98.71	98.71	98.28	94.40	97.73
		Bag	72.84	80.17	72.84	81.90	87.50	75.86	74.14	63.36	79.74	69.83	82.76	76.45
		Coat	28.02	64.66	37.93	41.81	59.91	46.98	52.16	46.55	42.67	50.43	91.81	51.18
	GGI	Mixed	65.23	81.47	70.26	74.14	82.04	73.28	74.14	69.54	73.71	72.84	89.66	75.12
		Normal	95.26	99.14	100.00	97.41	98.28	97.84	95.26	98.28	96.98	97.41	96.55	97.49
		Bag	73.28	83.62	72.84	84.48	87.07	78.88	69.83	61.64	81.47	70.26	84.05	77.04
		Coat	26.29	67.24	40.52	39.66	57.33	45.26	53.02	43.97	46.55	48.71	92.24	50.98
	GHGI	Mixed	64.94	83.33	71.12	73.85	80.89	73.99	72.70	67.96	75.00	72.13	90.95	75.17
7		Normal	96.12	96.55	95.26	94.83	95.69	89.22	88.36	93.97	95.26	95.69	96.12	94.28
		Bag	76.72	65.52	61.21	69.40	70.26	55.17	59.91	39.66	63.79	57.76	75.86	63.21
		Coat	71.55	72.41	59.48	30.17	54.31	44.40	47.41	29.31	43.97	39.66	50.43	49.37
	GEI	Mixed	81.47	78.16	71.98	64.80	73.42	62.93	65.23	54.31	67.67	64.37	74.14	68.95
		Normal	95.69	98.28	96.12	93.97	96.12	91.81	88.79	93.53	92.67	96.12	93.97	94.28
		Bag	75.00	61.64	59.91	68.97	70.69	53.45	52.16	39.66	57.33	55.17	77.16	61.01
		Coat	70.26	68.10	54.31	32.33	50.86	39.66	42.67	28.45	37.07	37.93	52.16	46.71
	GEnI	Mixed	80.32	76.01	70.11	65.09	72.56	61.64	61.21	53.88	62.36	63.07	74.43	67.33
		Normal	98.28	99.14	100.00	99.14	99.57	98.71	99.14	99.57	98.71	100.00	97.41	99.06
		Bag	76.29	77.59	75.00	86.64	92.24	83.19	68.10	63.79	79.31	75.00	92.24	79.04
		Coat	35.34	78.02	46.98	47.41	68.10	50.43	65.95	43.10	49.57	53.88	90.95	57.25
	GGI	Mixed	69.97	84.91	73.99	77.73	86.64	77.44	77.73	68.82	75.86	76.29	93.53	78.45
		Normal	97.41	99.14	100.00	99.14	99.14	99.14	98.28	99.57	98.28	100.00	96.55	98.79
		Bag	71.12	80.17	77.16	86.64	90.95	86.21	65.09	62.93	80.17	71.98	90.09	78.41
		Coat	37.07	78.45	43.10	49.14	68.10	53.45	61.21	50.00	52.16	52.16	90.09	57.72
	GHGI	Mixed	68.53	85.91	73.42	78.30	86.06	79.60	74.86	70.83	76.87	74.71	92.24	78.30
8		Normal	95.69	93.97	92.67	94.40	91.81	86.64	82.33	89.22	89.22	93.53	89.22	90.79
		Bag	69.40	49.14	59.05	51.72	69.83	41.38	32.76	44.40	50.00	66.38	59.91	54.00
		Coat	71.55	74.14	70.26	61.21	65.52	52.16	45.69	39.22	60.34	59.91	42.24	58.39
	GEI	Mixed	78.88	72.41	73.99	69.11	75.72	60.06	53.59	57.61	66.52	73.28	63.79	67.72
		Normal	95.26	92.24	90.95	93.53	90.52	83.62	81.47	88.36	90.95	92.67	88.79	89.85
		Bag	67.67	51.29	55.17	51.72	72.84	44.40	30.17	41.38	49.14	65.52	64.22	53.96
		Coat	70.26	73.28	69.83	57.33	65.52	50.00	48.71	33.19	54.74	57.76	40.95	56.50
	GEnI	Mixed	77.73	72.27	71.98	67.53	76.29	59.34	53.45	54.31	64.94	71.98	64.66	66.71
	GGI	Normal	96.12	96.98	98.71	98.28	98.28	93.53	96.55	99.14	96.12	96.98	93.97	96.79

		Bag	75.8	65.5	69.4	65.0	84.0	65.9	50.4	58.1	73.2	79.3	82.7	69.9
		Coat	81.9	83.1	80.1	64.6	75.8	70.6	61.2	55.6	71.9	75.4	68.5	71.7
		Mixed	84.6	81.9	82.7	76.0	86.0	76.7	69.4	70.9	80.4	83.9	81.7	79.5
		Normal	93.9	96.9	99.1	98.2	97.8	93.5	95.6	97.8	95.6	97.8	93.5	96.3
		Bag	71.5	69.4	69.8	64.6	81.9	64.6	54.7	57.7	74.5	74.1	88.7	70.1
		Coat	71.1	83.6	79.3	65.9	75.8	68.1	62.9	52.1	74.5	74.1	75.0	71.1
	GHGI	Mixed	78.8	83.3	82.7	76.2	85.2	75.4	71.1	69.2	81.6	82.0	85.7	79.2
		Normal	98.7	98.7	98.7	99.1	99.1	97.4	97.4	99.5	99.1	99.5	98.7	98.7
		Bag	89.6	92.6	93.1	97.4	96.1	89.6	94.8	97.8	93.1	92.6	90.9	93.4
		Coat	96.5	95.6	95.2	96.1	96.9	93.1	95.6	97.4	94.4	94.8	88.7	94.9
	GEI	Mixed	94.9	95.6	95.6	97.5	97.4	93.3	95.9	98.2	95.5	95.6	92.8	95.7
		Normal	99.1	98.2	98.7	99.5	99.5	96.9	98.7	99.5	98.2	99.5	98.7	98.8
		Bag	88.7	92.2	92.6	96.5	97.4	89.2	94.8	98.2	92.6	91.3	92.2	93.3
		Coat	95.2	96.1	93.5	96.5	96.5	93.5	95.6	97.4	94.4	95.6	90.0	94.9
9	GEnI	Mixed	94.4	95.5	94.9	97.5	97.8	93.2	96.4	98.4	95.1	95.5	93.6	95.7
		Normal	100.0	100.0	100.0	100.0	100.0	98.2	99.1	100.0	100.0	100.0	100.0	99.7
		Bag	96.9	98.7	98.7	98.7	96.5	95.2	95.6	98.7	96.1	94.8	96.5	96.9
		Coat	98.2	97.4	100.0	97.4	96.1	94.4	98.2	98.2	96.9	95.2	94.4	96.9
	GGI	Mixed	98.4	98.7	99.5	98.7	97.5	95.9	97.7	98.9	97.7	96.7	96.9	97.9
		Normal	100.0	100.0	100.0	99.5	100.0	97.8	98.7	100.0	100.0	99.5	100.0	99.6
		Bag	96.9	98.2	99.1	98.7	96.1	95.6	94.4	99.1	96.1	92.2	96.5	96.6
		Coat	98.2	97.4	99.5	98.2	96.5	95.6	97.8	98.7	96.9	94.4	94.4	97.1
	GHGI	Mixed	98.4	98.5	99.5	98.8	97.5	96.4	96.9	99.2	97.7	95.4	96.9	97.7
		Normal	98.7	98.7	98.7	98.7	99.1	96.5	96.9	99.5	99.1	99.5	98.7	98.5
		Bag	90.5	92.6	93.9	97.8	97.4	90.0	95.6	97.8	93.1	92.2	92.6	94.0
		Coat	94.8	95.2	96.5	96.9	96.9	93.5	94.8	97.8	94.8	94.8	90.0	95.1
	GEI	Mixed	94.6	95.5	96.4	97.8	97.8	93.3	95.8	98.4	95.6	95.5	93.8	95.9
		Normal	98.7	97.8	98.7	98.7	99.5	96.9	97.8	98.7	99.1	99.5	99.1	98.6
		Bag	90.0	93.5	93.5	96.1	97.8	92.2	94.4	98.7	93.1	91.8	92.6	94.0
		Coat	94.4	96.5	94.8	96.5	97.4	94.4	96.1	97.8	95.2	95.6	90.0	95.3
10	GEnI	Mixed	94.4	95.9	95.6	97.1	98.2	94.5	96.1	98.4	95.8	95.6	93.9	96.0
		Normal	100.0	100.0	100.0	100.0	100.0	98.2	99.1	100.0	100.0	100.0	100.0	99.7
		Bag	97.8	98.7	99.1	99.1	96.5	94.4	96.1	98.7	96.1	94.8	96.9	97.1
		Coat	98.2	97.4	99.5	98.7	96.1	95.2	98.2	99.1	96.5	95.6	94.8	97.2
	GGI	Mixed	98.7	98.7	99.5	99.2	97.5	95.9	97.8	99.2	97.5	96.8	97.2	98.0
		Normal	100.0	100.0	100.0	100.0	100.0	98.2	98.7	100.0	99.5	99.5	100.0	99.6
		Bag	96.5	98.2	99.5	98.7	96.9	95.6	96.5	99.1	96.1	92.2	96.1	96.9
		Coat	98.2	97.4	99.5	98.7	96.9	95.2	98.2	98.7	96.5	95.2	94.8	97.2
	GHGI	Mixed	98.2	98.5	99.7	99.1	97.9	96.4	97.8	99.2	97.4	95.6	96.9	97.9
		Normal	97.8	97.8	97.8	98.7	98.7	95.6	96.5	99.1	96.1	97.8	98.2	97.6
		Bag	93.9	95.2	92.2	96.9	96.9	95.6	96.1	97.4	94.4	93.9	91.8	94.9
		Coat	95.2	95.6	96.9	97.4	97.4	96.1	98.2	98.2	93.9	94.4	90.9	95.8
11	GEI	Mixed	95.6	96.2	95.6	97.7	97.7	95.8	96.9	98.2	94.8	95.4	93.6	96.1
		Normal	98.2	97.4	97.8	98.2	98.7	96.5	96.5	99.1	96.9	97.8	98.7	97.8
		Bag	92.6	95.2	90.9	96.9	97.4	94.8	95.6	97.8	94.4	94.4	91.3	94.7
		Coat	95.2	96.1	96.1	96.9	97.4	95.6	98.7	98.7	93.9	94.8	90.0	95.8
	GEnI	Mixed	95.4	96.2	94.9	97.4	97.8	95.6	96.9	98.5	95.1	95.6	93.3	96.1

		Normal	100.0	99.5	100.0	99.1	99.1	97.4	97.8	99.1	97.8	97.8	100.0	98.9
		Bag	96.1	98.2	99.1	97.8	99.1	93.9	97.4	99.1	96.1	96.9	96.5	97.3
		Coat	97.8	97.4	99.5	99.1	98.7	96.5	98.2	99.1	95.6	96.5	95.2	97.6
	GGI	Mixed	97.9	98.4	99.5	98.7	98.9	95.9	97.8	99.1	96.5	97.1	97.2	97.9
		Normal	100.0	100.0	100.0	98.7	99.1	96.5	97.8	99.1	97.8	97.8	100.0	98.8
		Bag	96.9	98.2	98.7	97.8	99.1	95.2	97.8	98.7	96.1	95.2	96.1	97.3
		Coat	98.2	96.9	99.5	99.1	98.7	97.4	98.2	99.1	96.1	96.5	95.2	97.7
	GHGI	Mixed	98.4	98.4	99.4	98.5	98.9	96.4	97.9	98.9	96.7	96.5	97.1	97.9
		Normal	96.5	97.4	96.5	98.7	96.9	89.6	95.6	99.1	96.5	97.8	96.5	96.5
		Bag	87.5	94.4	90.9	96.9	95.2	88.3	87.5	96.9	94.4	93.9	87.0	92.1
		Coat	92.6	94.4	97.4	95.6	95.2	85.7	96.1	97.8	93.5	92.6	89.6	93.7
	GEI	Mixed	92.2	95.4	94.9	97.1	95.8	87.9	93.1	97.9	94.8	94.8	91.0	94.1
		Normal	94.8	97.4	96.9	97.8	96.9	90.0	96.1	98.7	96.1	97.8	97.8	96.4
		Bag	87.5	93.9	88.7	96.1	94.4	87.9	88.3	97.8	94.8	93.5	87.5	91.8
		Coat	91.8	95.6	94.4	97.4	95.6	84.4	95.6	98.2	93.1	94.4	89.2	93.6
12	GEnI	Mixed	91.3	95.6	93.3	97.1	95.6	87.5	93.3	98.2	94.6	95.2	91.5	93.9
		Normal	99.1	99.1	100.0	99.1	98.7	94.8	97.4	99.1	97.8	97.8	100.0	98.4
		Bag	93.1	97.8	98.7	97.4	96.5	87.9	93.1	98.2	96.5	97.4	93.9	95.5
		Coat	97.8	96.9	99.5	97.8	96.9	89.2	98.2	98.7	95.6	95.6	94.8	96.5
	GGI	Mixed	96.7	97.9	99.4	98.1	97.4	90.6	96.2	98.7	96.7	96.9	96.2	96.8
		Normal	99.5	99.1	100.0	98.7	98.7	94.4	97.4	99.1	97.8	97.8	100.0	98.4
		Bag	93.5	97.4	98.7	98.2	97.4	88.7	93.5	97.8	96.5	95.6	93.1	95.5
		Coat	97.8	96.9	99.1	97.8	96.5	90.0	97.8	99.1	95.6	96.1	94.8	96.5
	GHGI	Mixed	96.9	97.8	99.2	98.2	97.5	91.0	96.2	98.7	96.7	96.5	95.9	96.8

C.7 Cross view gait recognition with GEI single part

		View Angle											
		0	18	36	54	72	90	108	126	144	162	180	Average
	Normal	72.26	77.00	89.07	90.56	82.68	80.92	83.93	89.58	91.93	90.09	86.83	84.99
	Bag	64.34	63.87	67.40	71.36	64.85	64.77	67.48	72.26	73.24	69.95	69.28	68.07
	Coat	71.04	68.77	71.24	72.34	63.40	60.97	62.81	71.28	73.79	70.92	70.96	68.87
1	Mixed	69.21	69.88	75.90	78.08	70.31	68.89	71.41	77.70	79.65	76.99	75.69	73.97
	Normal	55.72	55.53	68.06	74.33	75.67	72.06	73.55	78.02	77.63	73.59	70.38	70.41
	Bag	46.36	40.99	46.79	59.25	59.80	61.87	62.85	64.42	64.58	59.91	55.68	56.59
	Coat	56.23	44.40	50.35	57.76	61.21	61.05	60.62	64.77	61.72	60.38	60.85	58.12
2	Mixed	52.77	46.97	55.07	63.78	65.56	64.99	65.67	69.07	67.97	64.63	62.30	61.71
	Normal	64.03	61.44	73.08	80.45	74.65	69.44	75.00	81.47	82.25	79.35	74.41	74.14
	Bag	54.82	47.10	53.02	60.78	54.90	54.58	59.76	63.05	64.03	60.50	56.00	57.14
	Coat	49.41	44.36	42.52	42.05	35.42	31.82	37.46	41.14	45.85	46.32	44.71	41.91
3	Mixed	56.09	50.97	56.20	61.09	54.99	51.95	57.41	61.89	64.04	62.06	58.37	57.73
	Normal	70.14	66.73	80.33	85.31	81.39	77.82	80.60	85.89	87.11	84.64	81.43	80.13
	Bag	60.58	52.27	60.11	67.32	65.83	67.36	69.32	71.32	73.43	69.00	65.01	65.60
	Coat	61.32	52.19	55.05	57.72	56.19	54.39	56.43	63.05	64.42	62.93	61.95	58.70
4	Mixed	64.02	57.07	65.16	70.11	67.80	66.52	68.78	73.42	74.99	72.19	69.46	68.14
	Normal	67.28	69.40	80.80	86.87	78.37	77.04	80.84	84.84	85.74	82.17	79.39	79.34
5	Bag	58.19	53.84	59.44	65.56	59.29	60.89	64.50	66.18	68.53	61.40	60.15	61.63

	Coat	58.03	54.15	52.86	50.67	44.47	44.00	46.67	52.08	56.66	54.55	52.00	51.47
	Mixed	61.17	59.13	64.37	67.70	60.71	60.65	64.00	67.70	70.31	66.04	63.85	64.15
	Normal	68.69	72.53	82.76	88.32	79.31	78.21	82.09	86.68	87.46	83.82	81.74	81.06
	Bag	58.50	56.23	60.97	66.61	61.32	60.82	64.18	65.75	68.38	61.99	60.97	62.34
	Coat	56.82	54.58	54.15	52.19	48.00	47.34	48.55	52.78	56.58	54.19	51.80	52.45
6	Mixed	61.34	61.12	65.96	69.04	62.88	62.12	64.94	68.40	70.81	66.67	64.84	65.28
	Normal	71.90	77.66	86.72	91.22	83.93	82.21	85.11	89.85	90.87	88.91	84.95	84.85
	Bag	60.03	61.09	64.93	67.48	63.48	63.44	64.73	67.99	69.75	66.03	63.56	64.77
	Coat	63.79	60.46	59.40	56.78	50.59	49.33	49.96	56.82	60.66	59.33	57.84	56.81
7	Mixed	65.24	66.41	70.35	71.83	66.00	64.99	66.60	71.55	73.76	71.42	68.78	68.81
	Normal	63.36	67.12	84.13	87.97	79.90	76.29	83.11	86.79	86.72	86.48	82.21	80.37
	Bag	49.61	47.41	50.27	51.21	47.57	46.51	50.86	51.06	52.43	52.55	52.59	50.19
	Coat	61.09	56.70	58.19	54.62	48.39	46.00	50.20	54.15	59.40	55.13	54.51	54.40
8	Mixed	58.02	57.08	64.20	64.60	58.62	56.27	61.39	64.00	66.18	64.72	63.10	61.65
	Normal	59.25	65.24	81.66	85.11	73.28	69.91	74.53	81.90	82.45	80.68	80.33	75.85
	Bag	50.90	46.63	54.55	59.68	55.60	53.02	55.13	56.78	55.13	55.49	57.48	54.58
	Coat	60.82	57.09	62.74	65.56	56.23	52.39	56.03	60.89	62.77	59.13	59.72	59.40
9	Mixed	56.99	56.32	66.31	70.11	61.70	58.44	61.90	66.52	66.78	65.10	65.84	63.28
	Normal	55.84	61.91	77.63	81.27	70.06	66.69	70.81	77.31	79.11	76.61	75.98	72.11
	Bag	47.02	43.53	51.18	57.33	53.72	51.14	52.78	53.76	51.21	52.00	55.64	51.76
	Coat	59.01	54.47	61.36	64.77	55.29	52.23	54.04	59.64	60.70	57.84	58.74	58.01
10	Mixed	53.96	53.30	63.39	67.79	59.69	56.69	59.21	63.57	63.68	62.15	63.45	60.63
	Normal	39.15	44.79	59.09	64.97	55.68	52.51	54.98	59.68	58.66	52.04	55.88	54.31
	Bag	35.19	33.70	41.46	47.53	44.79	44.79	44.87	43.53	40.83	38.21	44.32	41.75
	Coat	43.65	43.46	47.88	53.76	48.16	46.24	46.59	49.37	47.57	43.73	47.53	47.09
11	Mixed	39.33	40.65	49.48	55.42	49.54	47.84	48.81	50.86	49.02	44.66	49.24	47.71
	Normal	39.85	45.57	58.93	65.36	55.45	52.00	55.41	59.52	60.50	52.66	55.41	54.61
	Bag	35.93	33.39	40.60	45.96	42.20	44.08	44.28	44.83	41.61	38.32	44.16	41.40
	Coat	43.10	42.83	47.84	53.49	46.36	45.38	46.24	50.39	48.67	43.73	46.71	46.79
12	Mixed	39.63	40.60	49.12	54.94	48.00	47.15	48.64	51.58	50.26	44.91	48.76	47.60