CHAPTER 5

Multiview issues in gait recognition

5.1 Introduction

One of the challenges in gait identification involves effective capturing of various perspectives of an individual's walking pattern to accurately ascertain its identity. Multiview gait recognition enhances recognition precision by collecting gait data from multiple camera perspectives. Nevertheless, multiview gait recognition presents several challenges, and a prominent one is the instability in perspectives and camera specifications, potentially resulting in variations in gait attributes. An additional concern pertains to the selection of the most informative vantage points, as not all perspectives offer equally valuable insights for recognition. Multiview gait recognition also presents obstacles such as the requirement for effective methods in feature extraction and fusion, along with addressing gait alterations stemming from alterations in walking speed, attire, object carriage, walking surface, and footwear. Nonetheless, despite these hindrances, recent years have demonstrated encouraging outcomes in multiview gait recognition, showcasing its potential to enhance the precision and dependability of gait recognition systems [86].

In this chapter, the challenges of multiview issues in gait recognition are addressed. A method for reducing the effect of multiview is developed using various existing gait representation techniques. One such method is the use of a model-free gait analysis approach. Also, we mentioned the effectiveness of the existing gait representation methods to tackle the influence of covariate conditions that need to be enhanced. Finally, view-invariant gait recognition using static and dynamic body keypoints is proposed, along with a technique to create an individual's unique gait pattern is formulated.

5.2 Mutliview issues in gait recognition

Multiview refers to the fact that people are usually observed from different viewpoints, and this can affect the accuracy of gait recognition. In other words, if the gait recognition system is only trained on a particular view of the subject's gait, it may not work well when the subject is viewed from a different angle. Figure 5.1 illustrates view angle representation with multiple cameras. It is seen from the figure that collecting data from different viewpoints involves capturing gait videos of the same person from different angles, such as front, back, and side views. In such instances, a change in the viewing angle results in the generation of a new set of features. Furthermore, if the angle change is substantial, the features represent a completely distinct set from the previous one. In addressing multiview issues in gait recognition viewing angle influences the most. In gait recognition, feature extraction is a critical step and different features can be extracted from different views of the same gait. For example, the angle of the knee joint may be more informative from the side view, while the stride length may be more informative from the front view. Therefore, a gait recognition system should extract features from multiple views and combine them to improve accuracy.

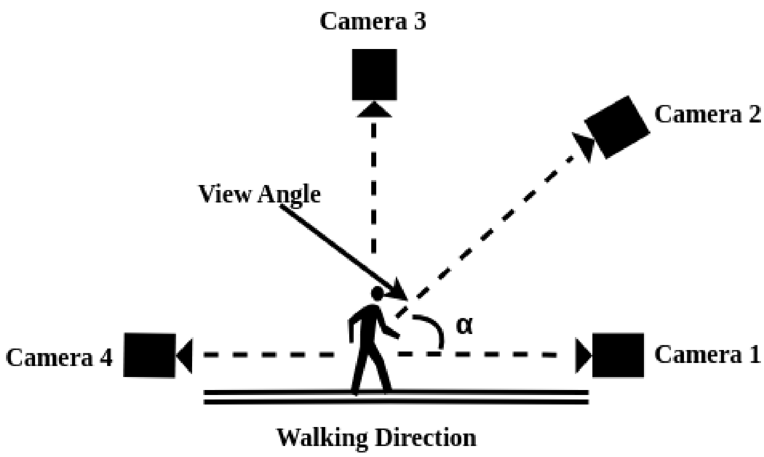

Figure 5.1: View angle representation

5.3 Propose framework

The proposed gait representation framework integrates GEI[31] and GGMI[4] gait templates to improve the accuracy of gait recognition algorithms in multiview with clothing and carrying covariate conditions. The gait silhouettes are first averaged across a gait cycle to produce GEI, which is then converted to GGMI. Secondly, using the HoG feature descriptor of 16*16 bin size the gait features are extracted from GGMI templates. Thirdly, Linear Discriminant Analysis(LDA) is used for dimension reduction and to determine a linear combination of features that characterize the classes, thus increasing the performance. Finally, the extracted features are classified by the Nearest Centroid (NC)classifier for different subject identification. The overview of the proposed framework is shown in Figure 5.2

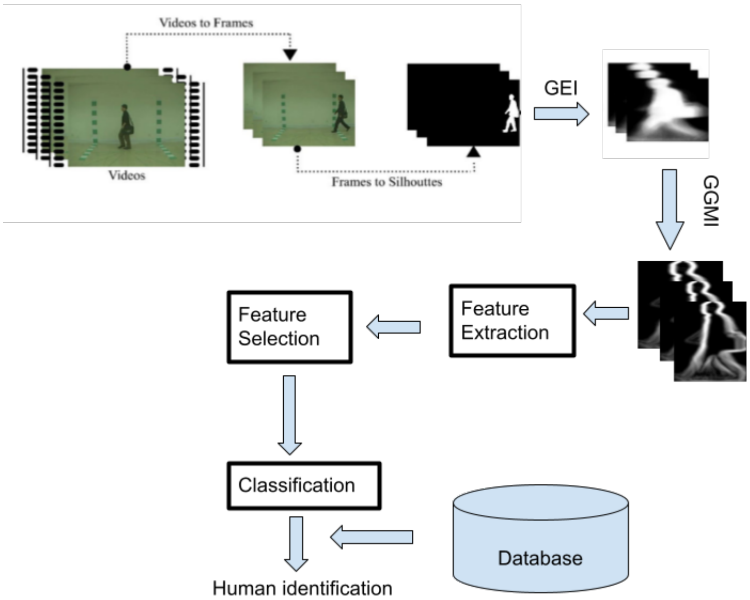

Figure 5.2: Proposed system for multiview gait recognition

5.3.1 GEI and GGMI template extraction

Low-dimensional features are an efficient approach for extracting and representing important aspects of gait patterns [4]. In this task, the focus is on using a Gait Energy Image (GEI), which is derived from a silhouette image and incorporates both static and dynamic features within the gait. The GEI is an enhanced spatial-temporal gait feature generated from silhouette image [30]. The GEI template is being adopted in this research work as an efficient template with other templates. Therefore, by employing the GEI gait template with a Gaussian filter and an edge detection operator, the GGMI (Gaussian Gait Magnitude Image) template is created.

5.4 Experimental Results

The experimental analysis is performed on CASIA B a standard dataset. The dataset has 124 subjects with 11 different view angles and three covariate conditions. Each view captures ten gait sequences for each person, including six usual walking sequences (Nm), two walking sequences in carrying a bag (Bg) condition, and two walking sequences in clothing condition (Cl). In Chapter 4, Figure 4.3 depicts normal walking, walking while wearing a coat, and walking with a carrying bag from the mentioned dataset. We created three experiment sets on this dataset, labelled EXPERIMENT-1,EXPERIMENT-2 and EXPERIMENT-3, to evaluate the impact of covariates on gait recognition performance and the robustness of our proposed gait template representation in handling viewing variation. The experiment sets are defined as follows:

- In the Experiment-1 , we have taken normal walk sequences from five different viewpoint(Nm1, Nm2, Nm3,Nm4 & Nm5) as training set and the others one walking sequence i.e Nm6 as probe set with viewing .
- For Experiment-2, we have taken the clothing covariates(Cl) as a test set, and the same training set as in the first experiment was used.
- Similarly for Experiment-3 we used the same training set and performed testing using the the carrying bag covariates(Bg).

Table 5.1, Table 5.2, and Table 5.3 indicate the correct classification rate evaluated using the NC classifier on the experiment sets.

To test the robustness of our proposed method an evaluation metric suggested Shiqi et al [104] is used in the task. C_Δ, which denotes the average of the correction classification on the diagonal(Gallery angle= probe angle]) in each of the experiment sets and is defined as:

$$C_{\Delta}^{NM} = \frac{1}{11}\sum_{n=0}^{5} C_{n}^{NM} \tag{5.1}$$

Table 5.1: Correct Classification rate for Experiment-1

		Probe angles										
Gallery Angle		0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
	0^0	99.19	65.04	36.59	15.45	8.13	1.63	3.25	8.13	5.69	15.45	30.08
	18^0	58.06	99.19	87.10	33.87	11.29	1.61	7.26	7.26	11.29	29.03	11.29
	36^0	18.55	79.03	99.19	78.23	26.61	11.29	7.26	13.71	29.84	16.13	7.26
	54^0	4.84	25	66.13	98.39	62.10	27.42	36.29	38.71	20.16	5.65	1.61
	72^0	2.42	9.68	18.55	69.35	100	93.55	71.77	39.52	9.68	1.61	4.03
	90^0	2.42	6.45	8.87	32.26	86.29	99.19	87.90	37.90	11.29	3.23	1.61
	108^0	1.61	2.42	8.87	31.45	68.55	89.52	100	70.97	27.42	3.23	3.23
	126^0	4.03	11.29	15.32	33.06	33.87	29.84	80.65	99.19	87.90	10.48	7.26
	144^0	7.26	19.35	26.61	23.39	12.90	8.06	26.61	83.87	99.19	25.81	8.87
	162^0	16.13	29.03	14.52	5.65	7.26	0.81	6.45	20.16	41.94	98.39	45.97
	180^0	30.65	14.52	9.68	7.26	4.84	4.03	5.65	8.87	12.10	59.68	99.19

Table 5.2: Correct Classification rate for Experiment-2

		Probe angles										
Gallery Angle		0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
	0^0	41.46	13.01	2.44	2.44	3.25	3.25	2.44	0.81	1.63	5.69	4.88
	18^0	14.52	42.74	23.39	10.48	1.61	3.23	4.03	4.03	2.42	7.26	5.65
	36^0	6.45	24.19	41.13	25.81	5.65	4.03	3.23	7.26	6.45	5.65	1.61
	54^0	3.25	8.13	26.83	47.97	13.82	8.13	7.32	10.57	9.76	1.63	1.63
	72^0	3.23	2.42	6.45	19.35	41.13	25.81	17.74	10.48	5.65	1.61	1.61
	90^0	2.42	0.81	5.65	11.29	27.42	34.68	25	8.06	5.65	1.61	0.81
	108^0	1.61	0.00	5.65	10.48	17.74	20.16	35.48	21.77	11.29	0.81	1.61
	126^0	3.25	3.25	7.32	8.94	5.69	7.32	13.82	26.02	21.95	6.50	4.07
	144^0	3.25	3.25	7.32	8.94	5.69	7.32	13.82	26.02	21.95	6.50	4.07
	162^0	6.56	5.74	4.10	2.46	3.28	1.64	5.74	7.38	7.38	36.89	13.11
	180^0	9.68	4.03	2.42	1.61	4.03	2.42	2.42	1.61	4.03	12.10	38.71

Where C_n^{NM} is the average CCR (correct classification rate) for Normal Walk. Similarly,

Table 5.3: Correct Classification rate for Experiment-3

	Probe angles											
		0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
Gallery Angle	0^0	85.37	45.53	26.02	12.20	5.69	3.25	1.63	5.69	3.25	9.76	15.45
	18^0	35.48	84.68	67.74	22.58	5.65	1.61	5.65	2.42	9.68	14.52	11.29
	36^0	12.90	48.39	86.29	58.06	16.94	6.45	6.45	10.48	18.55	9.68	4.03
	54^0	4.92	9.84	31.15	83.61	27.05	13.93	18.03	18.85	12.30	4.92	2.46
	72^0	1.61	8.06	10.48	42.74	83.06	65.32	49.19	17.74	8.06	1.61	2.42
	90^0	1.61	4.03	6.45	20.16	58.06	81.45	54.03	19.35	8.87	0.81	1.61
	108^0	3.23	2.42	8.87	25.81	39.52	56.45	79.03	40.32	15.32	5.65	2.42
	126^0	1.63	5.69	8.13	24.39	18.70	21.14	47.97	78.05	52.03	4.07	4.07
	144^0	4.84	8.87	12.10	11.29	5.65	6.45	17.74	49.19	83.87	13.71	9.68
	162^0	10.66	15.57	8.20	10.66	4.92	2.46	4.92	13.11	24.59	84.43	29.51
	180^0	15.32	11.29	8.06	3.23	3.23	1.61	6.45	6.45	12.90	37.90	83.87

Table 5.4: Average correct classification rate covering all the covariates

Nm (C_{Δ}^{NM})	Cl(C_{Δ}^{CL})	Bg(C_{Δ}^{BG})	Average
99.18	37.77	83.06	73.33

,

C_{Δ}^{BG} C_{Δ}^{CL} indicate the covariates with Bag and clothing respectively. The average of the Correct classification rate for each covariates are shown in 5.4.

5.5 View-invariant gait recognition using dynamic components keypoints

Gait recognition, an increasingly trending biometric identification method that analyses human gait patterns, has attracted considerable interest due to its non-intrusive nature and distinguishable characteristics. However, conventional gait recognition systems have limitations due to their reliance on fixed camera viewpoints, which reduces effectiveness in real-world scenarios with variable camera angles and positions. To overcome this limitation, view-invariant gait recognition has emerged as a viable solution, facilitating the identification and recognition of

Table 5.5: Comparison with other method

Methods	Nm	Cl	Bg	Average
GEnI[8]	98.3	33.5	80.1	70.63
CGI [90]	88.1	43.0	43.7	58.3
GEI-TM[104]	97.7	28.9	67.8	60.8
(GEI+GGMI)proposed method	99.18	37.77	83.06	73.33

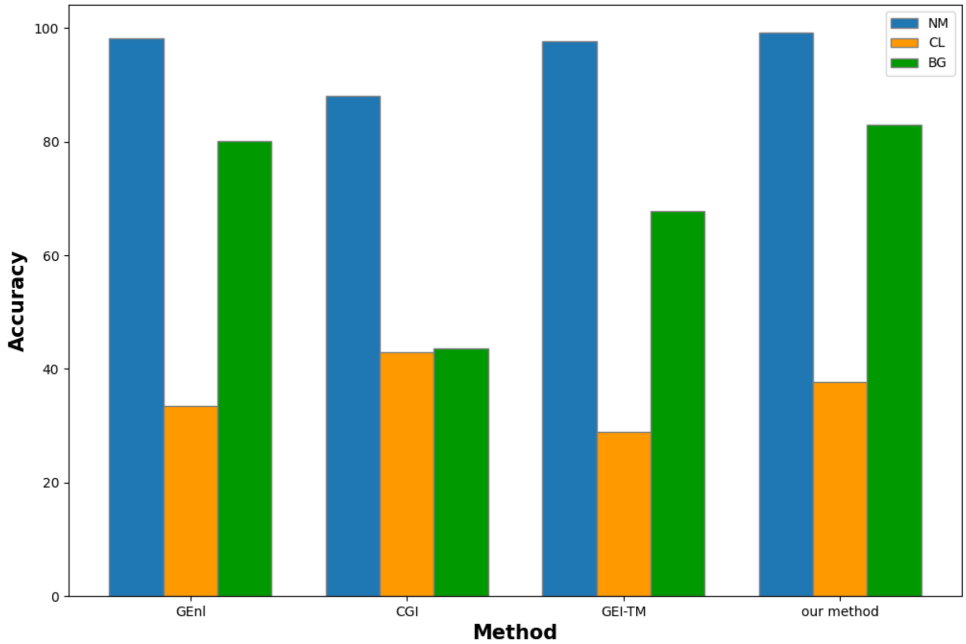

Figure 5.3: Comparison graph with other methods

individuals regardless of the camera's perspective.

Every person has a distinct walking style. The step distance and knee angle which differ from person to person, can be a used to create unique gait signature of an individual. In this task, we proposed to create a unique gait signature using dynamic feature vectors. The dynamic feature is generated from 10 prominent landmark body points (i.e., Left leg& Right leg: Hip-Knee-Ankle-Heel-Foot). Each individual's relative distances and angles will be calculated using body points. A part-based gait feature extraction from enhanced silhouette with angle calculation improved recognition rate[60]. Based on this work, we have evaluated two parameters from dynamic keypoints:(i) maximum step width during the initial stance phase and ii) minimum angle during the knee in the toe-off pre-swing phase. For evaluating the step width, we consider the left and right foot index. Figure 5.5 shows the representation of the maximum step width of a human movement. For the minimum knee angle calculation, we consider that the toe-off pre-swing which produces a minimum angle. The graphical representation of the gait cycle showing the teo-off pre-swing phase is depicted in figure **??**. The key points are then used for creating a sequence to evaluate angles of the right leg Hip-Knee-Ankle and indicated as R-knee° and for left leg Hip-Knee-Ankle (L-knee°) respectively. A sample depicting the hip, knee, and ankle joint of human walking is shown in figure 5.6.

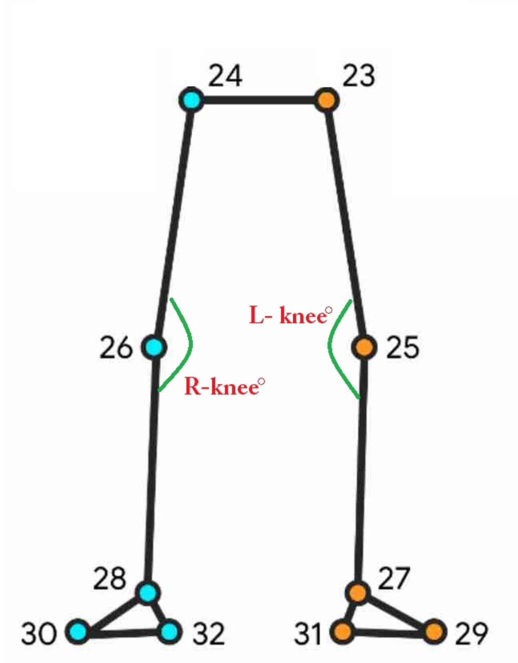

Figure 5.4: Dynamic pose estimation key points with Knee angles

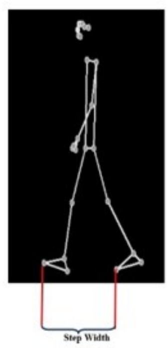

Figure 5.5: Representation of maximum step width of human walking

To achieve our task of creating a unique gait signature of an individual, the following equations are used to compute the angle between any given three key points.

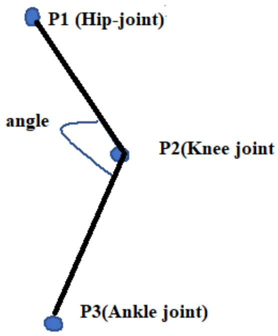

Figure 5.6: Hip, Knee and joints labeling forming an angle

Given P1 = (x_1, y_1), P2 = (x_2, y_2), P3 = (x_3, y_3) are keypoints where x and y are the coordinates of the key points. The angle θ for three key points is evaluated by using the following equations:

$$\overrightarrow{P1P2} = P2 - P1 \tag{5.2}$$

$$\overrightarrow{P2P3} = P3 - P2 \tag{5.3}$$

$$\overrightarrow{P1P2} \cdot \overrightarrow{P2P3} = \|\overrightarrow{P1P2}\| \, \|\overrightarrow{P2P3}\| \cos\theta \tag{5.4}$$

where, equation 5.2 evalautes the length between P1 and P2. equation 5.3 evalautes the length between P2 and P3. equation 5.4 implies the dot product of 5.2 & 5.3 Substituting 5.2 & 5.3 in 5.4 and θ is defined by the formula:

$$\theta = \arccos\left(\frac{\overrightarrow{P1P2} \cdot \overrightarrow{P2P3}}{\|\overrightarrow{P2P3}\| \, \|\overrightarrow{P2P3}\|}\right) \tag{5.5}$$

Accordingly, using landmark coordinates for the hip, knee, and ankle, the knee angle for both the left legs and the right legs is evaluated. Because of the symmetric and regular motion in human walking movement, the angle between the hip and the ankle can be considered to create unique characteristics for individual recognition irrespective of covariates issues. An individual completes a full gait cycle when both knee angle is approximately 180°%. The knee angle tends to decrease as the subject moves on, and after a minimal angle bend, it starts to increase until the knee is straight (i.e., 180°). The Figure 5.7 is the representation of one periodic movement in one complete gait cycle. The proposed framework, utilizing body point parameters to create a unique gait signature, is suggested to be an effective method for handling covariate issues. Further validation of this framework for gait analysis, particularly in addressing viewing covariate issues, can be explored in subsequent research.

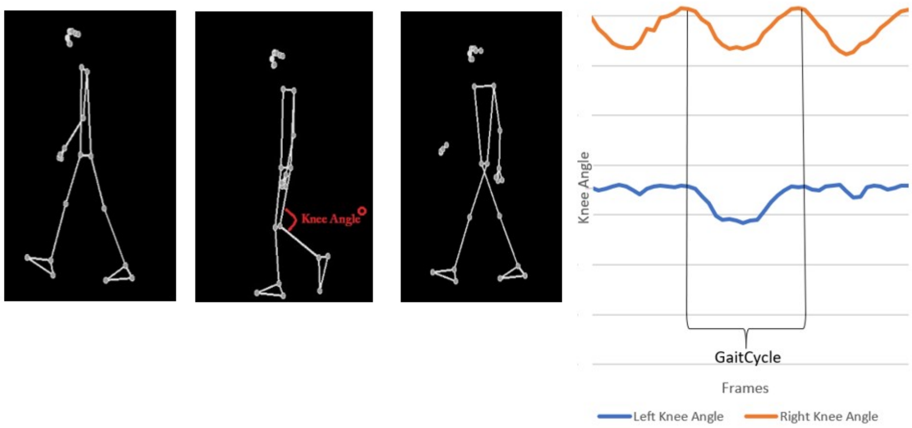

Figure 5.7: Graphical representation of Gait cycle

5.6 Summary

This chapter discusses the challenges and potential solutions in the field of multiview gait recognition. The main issue in gait identification is capturing multiple angles of a person's gait accurately to ensure correct identification. Multiview gait recognition aims to improve recognition accuracy by gathering gait data from multiple camera angles.

However, several challenges arise in multiview gait recognition. Fluctuations in views and camera characteristics can lead to variations in gait features, making it difficult to extract consistent information. Another challenge is determining which viewpoints provide the most informative data for recognition, as not all angles are equally helpful. Additionally, efficient feature extraction and fusion methods are needed, along with addressing gait variations caused by factors such as walking speed, clothing, carrying objects, walking surface conditions, and footwear.

Despite these challenges, multiview gait recognition has shown promising results in recent years and has the potential to enhance the accuracy and reliability of gait recognition systems. The chapter proposes a method for reducing the effect of multiview using various existing gait representation techniques. One approach mentioned is the use of a model-free gait analysis approach. The effectiveness of existing gait representation methods in handling the influence of covariate conditions is also discussed, emphasizing the need for improvement.

Furthermore, the concept of view-invariant gait recognition using static and dynamic body keypoints is discussed. It proposes a technique to create an individual's unique gait pattern, which can contribute to accurate identification in multiview scenarios.

The overall goal of the work presented in this chapter is to devise a gait representation method using dynamic key points. This method can improve the accuracy and reliability of gait recognition systems related to multi-view gait identification.