Trait of Gait: A Survey on Gait Biometrics

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Abstract

Gait analysis is the study of the systematic methods that assess and quantify animal locomotion. The research on gait analysis has considerably evolved through time. It was an ancient art, and it still finds its application today in modern science and medicine. This paper describes how one's gait can be used as a biometric. It shall diversely cover salient research done within the field and explain the nuances and advances in each type of gait analysis. The prominent methods of gait recognition from the early era to the state of the art are covered. This survey also reviews the various gait datasets. The overall aim of this study is to provide a concise roadmap for anyone who wishes to do research in the field of gait biometrics.

Keywords— gait pathology, kinematics, kinetics, clinical gait, EMG, gait biometrics

1 Introduction

The simplest definition of gait states that it is the manner and style of walking [1]. This can refer to any animal that can walk whether bipedal or quadrupedal. It can be more sophisticatedly defined as the coordinated cyclic combination of movements that result in locomotion [2]. This definition can be equally applicable to any form of activity that is repetitive and coordinated so as to cause motion of the living being originating it. Gait can vary from walking, running, climbing and descending the stairs, swimming, hopping and so on; all of which follows the same principle in this definition. In the context of this survey, the word 'gait' generally refers to the 'walking gait' of a human.

Recent research has proved that gait can be used as a non-obtrusive form of biometric [2]. The Defense Advanced Research Projects Agency (DARPA) launched the Human Identification at a Distance (HumanID) programme in the year 2000 (ended in 2004). This research programme focused on human identification through the face, gait and the application of new technologies. The intention of the programme was to use the state of the art unobtrusive distance biometric techniques

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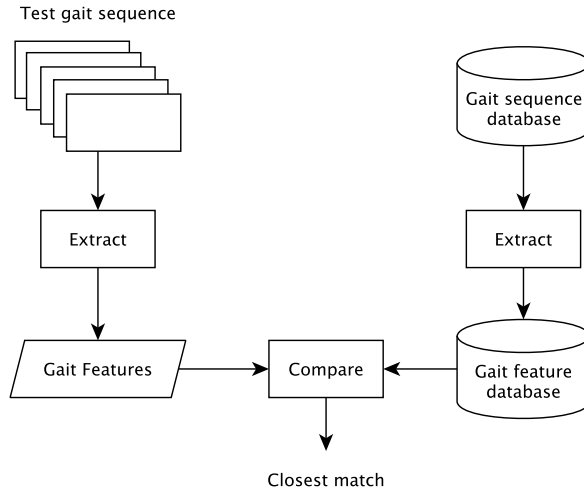[d]*Anna University, Chennai, India.* e-mail: `easwarakumarks@gmail.com`

Figure 1: Simplified gait recognition system

on real world data. Gait-based recognition played a significant role in here. Major institutions which took part in this program are MIT, CMU, USF, UMD, Georgia Institute of Technology, and the University of Southampton [3]. The datasets compiled by most of these institutions are publicly available. Section 5 discuss more on those datasets.

Gait is characteristic to one's individuality it is considered to be an accepted form of unobtrusive biometrics [2]. Hence, in theory, it does not require the cooperation nor the awareness of the individual being observed. A simplified template for a gait recognition system is as shown in Figure 1. A gait sequence is a temporal record of an person's gait. It can be a sequence of frames of a video or point-light motion, or foot pressure and foot placement pattern. These are usually translated into a feature database after some means of preprocessing and feature extraction. When the test gait sequence is given for identification, the system refers the gait feature database and returns the closest match (if any) according to some criteria. If the similarity between test gait and stored gait are used as a measure, the closeness can be determined by formulating a threshold. Gait recognition systems are sometimes evaluated in terms of the ranks to which the true identities are resolved. For instance, rank-1 implies the true gait is identified as the first closest match, while rank-k implies that the true gait was identified within the k closest matches from the database [4].

Gait recognition can be broadly classified into two types: model-based and model-free. Due to its simplicity and efficiency in use, model-free methods are more prevalent. We further categorise model-free techniques as template-based and non-template methods.

Many benchmark datasets are available to compare the performance of one algorithm with another. The details of such databases are available in section 5.

2 Inhibiting Factors

Certain factors inhibit the effectiveness of biometric gait recognition by confounding the features that can be observed [2]. The following briefly explains each factor with relevant research on how they deviate the parameters of gait.

Walking surface. Studies show that when the surface is unstable, such as a wet surface, the walking speed, toe-in angle and step length are significantly reduced to retain control over balance [5]. However, when walking on other irregular surfaces like grass, foam or studded with small obstacles, walking speed can be maintained with a variable cadence and a longer stride length [6]. Even two regular surfaces such as vinyl and carpet have a significant difference [7]. In slippery surfaces, reductions can also be observed in stance duration, load supporting foot, normalised stride length [8].

Footwear. When the footwear is considerably different, so is the gait of the individual. This especially concerns high heel users. To maintain their stability, people wearing high heels require more control over their centre of mass [9] and tend to have longer double support times [5]. Recent studies show that habitually shod walkers and habitual barefoot walkers exhibited a significant gait difference when switching their footwear in terms of their stride length and cadence [10].

Injury. When any portion of the lumbar region or lower limb is injured, the individual naturally adopt an antalgic gait. The individual walks in a way so as to avoid the pain caused by the injury. This style of walking restricts the range of motion of the associated limb leading to a deviation in the usual gait proportional to the magnitude of the injury. In-depth research on how injury affects gait is provided by Ruoli Wang's thesis [11].

Muscle development. The development of muscles gives a different range of control over the parts of the body that affects gait. The sheer mass of the muscles developed alter the centre of mass at the associated mobile limb as well as the body itself. The shift depends on the difference in mass. The change in the centre of mass can modify the inclination of pressure required for proper stability [12]. An extensive study on the correlation between muscle mass with gait performance [13] proves that muscle mass directly relates to gait speed, especially in the case of geriatric patients.

Fatigue. When the individual is subjected to fatigue, the stability of the concerned gait decreased while a noticeable increase in variability of gait is exhibited [14]. The time taken for the recovery towards normal gait depends on the extent of exertion applied to the individual so as to get to a fatigued state and the individual's stamina. This aspect was observed from Ashley Putnam's thesis [15] in which a study with army cadet treadmill protocol was conducted to analyse the effect of exhaustion on gait mechanics and possible injury. Cadets ran till exhaustion and had their gaits observed. The resulting gait had both inter- and intra-variable vertical stiffness in the lower limbs.

Training. When the individual is subjected to some form of physical training, it is possible that her/his gait is also subjected to change. This change can be evident as a result of military training, prolonged load condition, prolonged use of particular footwear and athletic training.

Extrinsic control. Humans have an ability to control their gait to an extent so as to differ from their usual gait. A person can mince walk, and depending on how self-aware the individual may be she/he can walk with a swagger or strut, a brisk walk or tip-toe. Another matter to note is the level of awareness the individual have of his/her surroundings. This would correspond to the tendency to alter gait while self-control correlates with the degree to which the gait can be altered by the
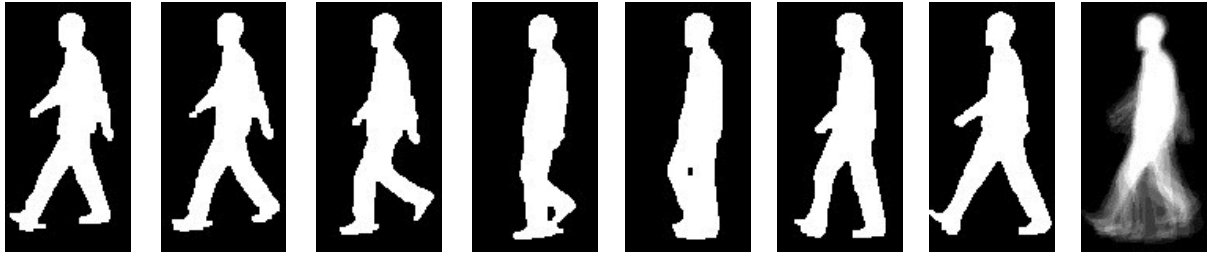
Figure 2: The Gait Energy Image of a gait sequence over a single gait period. The last image is the GEI template where the first seven sequences depict successive normalised frames of gait.

individual. This factor explains how members of the army can synchronise gait during a march.

Intrinsic control. There are elements that can control a person's gait in such a way that the individual is sometimes unaware of the change that takes place. The best example of this case are emotional responses or mood of the individual: state of happiness, sorrow, anger or any other emotion strong enough to make an impact on one's gait. The variability can range from subtle to significant and can vary from one person to another. Related studies are provided in [16].

Age. Although the factor may not contribute to change in gait over a short period, it certainly does influence gait to a large extent. Ageing, in general, causes musculoskeletal and neuromuscular losses. To compensate for these losses, the individual make certain adjustments which can be observed in the individual's gait [17].

Clothing. While the change of clothing does not necessarily modify the gait for slight differences in weight, it might, however, show changes in the associated silhouettes. This change would affect a major portion of gait recognition algorithms that depends on the spatial configuration of silhouettes. However, a greater change in the weight of the clothing, such as a winter suit, has a higher probability of affecting the gait itself.

Load. The effect of load can significantly influence gait. In a loaded condition such as wearing a backpack, the individual is subjected to a higher weight in addition to his/her body weight. In order to regulate locomotion, the foot exerts higher pressure during plantarflexion generating a greater ground reaction force than the unloaded condition [18]. Apart from the pressure applied, the body must cope with the change in balance for a stable gait [19]. The load can also be asymmetrical, such as a wearing a handbag, cross-bag or shoulder bag, or carrying a suitcase. In this case, a greater difference in the pelvic rotation is observed [20]. The body shifts the pelvic movement so as to counteract the imbalance caused by the load.

3   Model-free techniques

The vast majority of model-free techniques tend to have a strong reliance on spatiotemporal analysis of silhouettes of the individual during gait. A spatiotemporal analysis takes into account the variation in the spatial domain with respect to that in the time domain. So when this is applied in gait recognition, the analyses involves the observation of the spatial locations of body parts and

their movement in different stages in time.

Nearly all model-free methods have background subtraction and silhouette extraction as the first step. Background subtraction is a simple method in which the change in pixel values between one frame and the successive frame is observed to bring out only the objects that are seen in motion. From these objects, the moving human silhouette can be extracted. The result of background subtraction is usually binarized in which the moving object seems to be white and the background is black, or vice versa in some cases like the USF HumanID silhouette database.

The novelty mainly lies in how the features are extracted. The recognition process involves the use of an established machine learning algorithm such as the nearest neighbour classifier (used in [21–28]), and HMM (used in [29–33]). Some apply different techniques such as canonical analysis [34, 35], spatiotemporal correlation [36], and DTW [25, 37, 38]. A few others devise newer techniques for closeness representation.

3.1 Earlier methods

The earliest known spatiotemporal gait recognition techniques were published during the 90s. Niyogi et al. [22] proposed to recognise gait at a sagittal angle with the subject walking frontoparallel. It is a template-based method which modelled the human gait in the form of a set of spatiotemporal snakes [39] from the slices of the moving parts of the human contour along the time domain. They expressed the spatiotemporal dimensions as XYT signifying the 2D (x, y) spatial coordinates varying with respect to time t. The recognition they have obtained with 26 image sequences across five human subjects reaches up to 83%.

J. Little and J. Boyd [40] introduced the concept of optical flow in gait recognition. In principle, the points in the image sequence that vary with time tend to oscillate periodically during the subject's gait. By observing the optical flow of these points, the m time varying scalars can be produced. From these scalars, the phases of the oscillations $\phi_1, \phi_2, ..., \phi_m$ can be extracted. The phases are normalised with respect to a reference phase ϕ_m to form the feature vector $F = (F_1, F_2, ..., F_{m-1})$ where $F_i = \phi_i - \phi_m$. Hence F is used to represent the gait instance. They reached a higher recognition rate of up to 95% by testing their technique with seven instances for each of six human subjects.

An earlier version of template matching method was proposed by P. S. Huang et al. [34]. They used the Eigenspace transformation (EST), as adopted by Murase and Sakai [36], to convert the gait taken as a sequence of images to a template called the 'eigengait'. On top of this, canonical space transformation is applied with generalised Fisher linear discriminant function to separate the classes boundaries required for prediction. However, they also seemed to use the small dataset used by Little and Boyd for their application to show a questionable accuracy of 100%.

Static features are those that do not change over the temporal domain. These include features such as the height of the person, the length of the limbs. Johnson and Bobick [41] used static features to obtain a recognition rate of 94% with an expected confusion of 6.37%. The experiment involved placing cameras at each of two different locations; near and far. 18 human subjects were made to walk three times each and were observed at the two oblique angles. The features determined were the height of the bounding box, the Euclidean distance between the head and pelvis, maximum length between the pelvis and either of the feet, and the distance between the left and right foot.

Though the above methods show attractive recognition rates, all the methods proposed at those times before suffered one major drawback: their accuracies are biased to their samples which are too small when considering the application as a biometric.

3.2 Template-based methods

These are a class of methods that involves transforming the sequence of silhouette images taken from a gait video to a single image that holds the composition of the motion-related features of the sequence.

Hayfron-Acquah et al. [21] assessed the symmetry of the extracted silhouette using a generalised symmetry operator. The contours of the silhouette are extracted by applying Sobel edge detection function. From the sequence of contours obtained, a symmetry map is produced. Euclidean distance between Fourier descriptors is used as a similarity measure for gait recognition. They used the SOTON database for their experimentation and had attained a correct classification rate (CCR) of 97.3 % for $k = 1$ and 96.4% $k = 3$ using the nearest neighbour classifier.

L. Wang et al. proposed a unique method to recognise gait by analysing the contours of the silhouettes [42]. The CASIA dataset A was used in this experiment. The shape of the contour of a given silhouette sequence is converted to a template with the use of Procrustes shape analysis. Different exemplars are created for each viewpoint. They tried three types of nearest neighbour algorithms, viz., NN, kNN, and ENN (NN with class exemplar), in which ENN provided the best results for gait recognition.

Experimental results of Cuntoor et al. [60] suggests that Dynamic Time Warping (DTW) and Hidden Markov Model (HMM) can be combined to produce a better gait recognition result. DTW was used to align the motion of the arms and legs to normalise the phase of gait while HMM is used to define the leg dynamics.

The efforts of the University of South Florida [43] has brought forth a new revolution to gait recognition. They compiled the USF Gait Challenge dataset which consists of 1,870 gait sequences obtained from 122 human subjects over 5 types of variation. The dataset was categorised to 12 challenge probe sets for experimentation and a gallery set for training. A simple baseline algorithm was developed to facilitate users of the dataset to compare the performance of gait algorithms effectively. The algorithm involves the use of the Tanimoto similarity measure (Eq 1) to guage the similarity between two silhouettes.

$$Sim(p, q) = \frac{|p \cap q|}{|p \cup q|} \tag{1}$$

Here, p and q are two binarized images where each image is represented as an ordered set of pixel values. Their intersection corresponds to the number of pixels that are the same in their silhouettes. Their union provides the total number of pixel space taken when both silhouettes superimpose. The correlation between the silhouette similarities provides the measure of closeness used for the recognition step. Further details of the USF Gait Challenge dataset is provided in section 5.

The most notable form of silhouette-based gait recognition techniques uses the production of

6

Table 1: Template-based Methods for Gait Recognition

S.No.	Year	Study	Technique	Plane	Dataset
1.	1994	Niyogi et al.	Fitting of spatiotemporal snakes	Sagittal	$5s \sim 26$ seq.
2.	1996	Murase & Sakai	Parametric eigenspace transformation	Sagittal	$7s \times 10i = 70$ seq.
3.	1999	P. Huang et al.	Canonical and eigenspace transformation	Sagittal	UCSD
4.	2003	L. Wang et al.	Procrustes shape analysis	Multiview	CASIA-A
5.	2005	S. Sarkar et al.	Gait Baseline	Sagittal	USF, CMU
6.	2006	Ju Han & Bir	Gait Energy Image (GEI)	Sagittal	USF v1.7, v2.1
7.	2007	T. Lam et al.	MSCT and SST	Sagittal	USF v1.7, v2.1, SOTON
8.	2008	X. Yang et al.	Enhancing GEI through dynamic regions	Sagittal	USF v2.1
9.	2009	Kusakunniran et al.	Weighted Binary Pattern (WBP)	Sagittal	CMU, CASIA-A,C
10.	2010	Bashir et al.	Gait Entropy Image (GEnI)	Sagittal	CASIA-B, SOTON
11.	2010	E. Zhang et al.	Active Energy Image (AEI)	Sagittal	CASIA-B, CASIA-C
12.	2011	T. Lam et al.	Gait Glow Image (GFI) using optical flow	Sagittal	USF v2.1
13.	2011	Zheng et al.	View transformation model using GEI	Multiview	CASIA-B
14.	2012	C. Wang et al.	Chrono-Gait Image (CGI)	Sagittal	USF, SOTON, CASIA-B
15.	2013	N Liu et al.	GEI-based Multiview Subspace Representation	Multiview	CASIA-B, CMU-MoBo
16.	2013	Dupuis et al.	GEI subsetting using random forests	Multiview	CASIA-B
17.	2014	Hofmann et al.	Depth Grad. Hist. En. Img. (DGHEI) with audio	Sagittal	TUM-GAID
18.	2014	Aqmar et al.	Gait Fluctuation Image (GFlucI)	Sagittal	OU-ISIR-D, OU-ISIR-LP
19.	2015	P. Arora et al.	Gait Information Image (GII) features	Sagittal	OU-ISIR, SOTON, CASIA-B
20.	2015	X. Xing et al.	Canonical correlation analysis of GEI	Multiview	CASIA-B
21.	2015	P Yogarajah et al.	Joint sparsity model and l1-norm'	Sagittal	CASIA-B
22.	2015	S.D. Choudhury et al	View-invariant multi-scale gait recognition	Multiview	CASIA-B
23.	2016	Zhao et al.	Walking Path Image (WPI)	Multiview	CASIA-B
24.	2016	I. Rida et al.	GEI segmentation using group lasso motion	Multiview	CASIA-B
25.	2016	K. Shiraga et al.	GEINet – CNN on GEI	Multiview	OU-ISIR-LP
26.	2017	C. Li et al.	DeepGait – VGG-D on GEI with Joint Bayesian	Multiview	OU-ISIR-LP
27.	2017	Z. Wu et al.	Ensemble of CNN, GEI and temporal features	Multiview	OU-ISIR-LP, CASIA-B

Note: The terms 'i' and 's' stands for instances and human subjects respectively for the set of sequences (seq.) in the dataset.

a Gait Energy Image (GEI) template [4] from the gait cycle. Technically, the GEI shows how energy is dissipated spatially through the stages of the gait cycle. It is so prevalent in literature such that silhouette based methods that are published after its time (2006) can be classified either as GEI-based or non-GEI-based.

Given a sequence of N homogeneous gait silhouettes of pure black and white colour definition of a single gait instance, $B_t(x, y)$, the GEI can be expressed as

$$G(x, y) = \frac{1}{N} \sum_{t=1}^{N} B_t(x, y) \tag{2}$$

It is created by superimposing the pixels of silhouette sequence of a given gait by summing the values and averaging them resulting in the output as a grey-level image of proportional pixel intensities. The term homogeneous in here refers to the constraint that all images of the ordered gait sequence must be of the same dimensions. Hence the final stage boils down to image comparison of the test GEI with the GEIs in the gait database. An example of a GEI obtained from a subject's gait from the CASIA-B dataset along the sagittal plane is as shown in Figure 2. The real GEI as illustrated is not used for the comparison. Instead, a synthetic template is produced with an addition of noise and removal of the feet region to cope up with the changes in walking surface, shoe type, and clothing. The features are learned based on Multiple Discriminant Analysis (MDA) after passing through Principle Component Analysis (PCA) for dimensionality reduction. The Euclidean distances towards the class centres with respect to the features provide the closeness measure for recognition. Experimental results of Ju Han et al. [4] show recognition rates averaging around 55.64% using the USF Gait Challenge v2.1 database.

In about the same time, T. H. Lam et al. were developing their version of gait feature templates using motion silhouette contour templates (MSCTs) and static silhouette templates (SSTs) [23]. The characteristics that capture motion are represented in MSCT while SST depicts the static characteristics of the human gait. They did seemingly perform well for both indoor and outdoor applications. But soon after the article was published just after, they noticed that their method was not as accurate as the GEI. Hence they developed a whole new technique called the gait flow image (GFI) based on optical flows for a better performing biometric system [25]. For Rank 1, the CCR of SST and MSCT was 29.75% and 34.00 respectively, whereas GEI in their experimental observation gave a CCR of 39.08% which was outperformed by the GFI method with a recognition rate of 42.83%.

X. Yang et al. [24] show that the original GEI technique can be enhanced if just the dynamic area of the GEI template is extracted for feature production. Using this enhancement, they were able to produce an effective recognition rate of 55.64% tested against the USF Gait Challenge v2.1 database. Hofmann et al. [61] combine colour histograms with the GEI to be able to identify and track gait even through the situation of occlusion. This method was verified using their dataset called TUM-IITKGP.

The many studies then published their own version of an energy image adopted from the core principles of the GEI. One of such proposals includes the GFlucI – gait fluctuation image [52]. By applying a technique called Self-DTW, a variant of DTW, the silhouette sequences are phase-normalised. These sequences are then converted to a template called the GFlucI which incorporates only the spatial and temporal fluctuations in gait. Once a GEI template is formed, the

temporal characteristics of gait are lost. A chrono-gait image (CGI) was proposed to incorporate this temporal information to the GEI in [48]. The motion history image (MHI) [62] originally proposed for action recognition is specialised for gait recognition in [33]. More examples include the gait entropy image (GEnI) [45] and active energy image (AEI) [46].

The information from a depth camera can be combined with that of an RGB camera to provide a richer set of features for gait recognition. Hofmann and his team [63] have applied this notion and formulated a new technique for producing a GEI-like image called the depth gradient histogram energy image (DGHEI). It is produced by collating the histogram of oriented gradients (HOG) of every image in the gait sequence to produce a single gait template for comparison. Despite the fact of being a weaker biometric indicator, audio-based data from gait, by itself, can estimate a range of soft biometrics such as age, height, gender, and shoe type. Later in [51], DGHEI was combined with audio data to be able to extract further distinguishing information to aid in gait recognition.

There is an inherent uncertainty in certain regions associated with a gait feature template for a given individual. This notion is exploited by P. Arora et al. [28]. Their work involves the production of a GEI-like gait template over a single gait cycle called the gait information image (GII) to generate features based on Hanman–Anirban entropy function [64] – a modified version of Shannon's logarithmic entropy function [65]. This GII gives rise to two feature templates, the energy feature (GII-EF) and the sigmoid feature (GII-SF). The statistics of the motion patterns of these two templates are hence used to make the prediction with the conventional nearest neighbour classifier.

Re-identification is another important scenario in biometric gait analysis. In a common video surveillance network, a person can be observed from many angles as she/he moves from the visual range of one camera to another. The challenge in addition to analysing the gait based recognition is to be able to track the individual through the different angles over the network of cameras. The work of Zheng Liu et al. [66] addresses this research problem by combining the GEI template's ability to match gait along with Gabor features and HSV histograms to match appearance. Features are matched hierarchically with descriptors for matching. The metric learning method was used as an alternative to the nearest neighbour classifier.

3.3   Non-template methods

Though found to be efficient in practice, not all silhouette-based methods in literature involves the production of a template image. We shall discuss some of them here.

J.P. Foster et al. [35] have claimed to have attained recognition rates above 75% by running experiments on 114 subjects of the SOTON video gait dataset. Their method monitors the temporal changes in the areas of the clipped gait window segmented by masked sectors. Using these time-varying area metrics, they formulate a feature vector for recognition.

A framework for joint tracking and event detection using maximum a posteriori (MAP) hypothesis was suggested in [67]. Although not proposed as a gait recognition technique, this method would be able to produce an efficient gait recognition technique if utilised in such a way. Four events were modelled corresponding to the different directions of walking concerning the point of view: walking towards the camera, walking away from the camera, walking from left to right and from right to left. The corresponding HMM was trained and validated using the UMD Dataset 1.

Table 2: Non-template Methods for Gait Recognition

S.No.	Year	Study	Technique	Plane	Dataset
1.	1998	J. Little & J. Boyd	Phase difference of optical flows	Sagittal	UCSD
2.	2001	Johnson & Bobick	Static body parameters	Multiview	Georgia Tech
3.	2002	A. Kale et al.	Frame to exemplar distance (FED)	Sagittal	CMU, UMD
4.	2003	J. P. Foster et al.	Temporal change in segmented areas	Sagittal	SOTON: $28s \times 4i = 112$
5.	2003	L. Wang et al.	PCA-based eigenspace transformation	Multiview	CASIA-A
6.	2004	A. Kale et al.	FED with outer contour width	Sagittal	CMU, USF, UMD
7.	2004	R. Wang et al.	Joint-tracking via MAP hypothesis	Multiview	UMD
8.	2006	N. V. Boulgouris et al.	Linear time normalisation	Sagittal	USF
9.	2006	Zongyi Liu & S. Sarkar	Population HMM	Sagittal	USF, CMU, UMD
10.	2007	N. V. Boulgouris et al.	Matching of body components	Sagittal	USF
11.	2007	Zongyi Liu & S. Sarkar	Population EigenStance-HMM	Sagittal	USF, CMU
12.	2013	Choudhury & Tjahjadi	Shape and motion analysis of contours	Sagittal	USF
13.	2014	Nguyen et al.	HMM of motion history image (MHI)	Sagittal	CASIA-A
14.	2015	Chin P. Lee et al.	Transient binary patterns (TBP)	Sagittal	CASIA-B, OU-ISIR-D, CMU
15.	2016	Zeng & Wang	Periodic deformation of human gait shape	Multiview	CASIA-B, CMU-MoBo
16.	2016	Muramatsu et al.	Frequency domain features of joint-subspace	Multiview	OU-ISIR-LP

Table 3: Model-based Methods for Gait Recognition

S.No.	Year	Study	Type	Technique	Plane	Dataset
1.	2001	Rawesak T. & Bobick	Marker	Time-normalized joint trajectories	Sagittal	Georgia Tech
2.	2002	Z. J. Geradts et al.	Marker	Multi-planar gait parameter extraction	Multiview	$11s \times 2i = 22$ seq.
3.	2003	Rawesak T. & Bobick	Marker	Speed-invariant gait parameters	Sagittal	$15s \times 36i = 540$ seq.
4.	2007	R. Zhang et al.	Silhouette	Five-link biped human model	Sagittal	USF, CMU
5.	2008	M. Goffredo et al.	Silhouette	Geometric marker-less joint estimation	Multiview	CASIA-B
6.	2015	P. Chattopadhyay et al.	Kinect	Combining depth and silhouette features	Frontal	$29s \times 8i = 232$ seq.
7.	2015	D. Kastaniotis et al.	Kinect	Euler angles, dissimilarity space mapping	Oblique	UPCVGait

Note: Model-based features can either be extracted through 3D cameras with the subject fitted with IR or bulb *markers*, articulation points inferred from *silhouettes*, or depth information from Microsoft *Kinect*.

In the work by N. V. Boulgouris et al. [70], a low dimensional feature matrix is represented by accounting the average distances from the centre of the silhouette. Each silhouette is represented as a feature vector which is composed of a sequence of angular transforms made on segmented angular slices $\Delta\theta$. The dimension of each vector is $K = 360/\Delta\theta$. The feature matrix is produced by collating the vectors of each silhouette in the sequence of frames. Hence each column would represent a frame, which each row would depict the change in the angular transform for a given angular slice. In the USF gait challenge dataset, a period in the gallery (reference) is not equal to that of the probe sequence (test). Hence, a technique called linear time normalisation was utilised to make the feature matrix of each probe and gallery sequence comparable by compensating for the difference in the sequence length. The same method is used in their next paper [71] but with a different feature extraction technique. In this work, the body as depicted in the silhouette is segmented into components. The components are ranked with according to their proportional relevance during the comparison operation.

The work of Zongyi Liu and Sudeep Sarkar [29] promoted the fusion of face and gait biometrics. A subset of the USF dataset was used for this purpose. The exemplars, in this case, are not obtained from a single template but a specified stances analogous to the formally depicted gait cycle. These stance frames are modelled using a population EigenStance-HMM; a method that is extended from their previous technique, population HMM [31]. The entire population of the training set is fed in the learning phase. A given gait silhouette sequence can be segregated into these stance models by K-Means clustering with Tanimoto distance as the distance measure. A cyclic Bakis variant of HMM was modelled for the gait recognition. This gait recognition algorithm was used in combination of face recognition using Elastic Bunch Graph Matching (EBGM) based on Gabor features to attain a much higher performance over the Gait Challenge baseline algorithm when compared using the toughest sets of the USF Gait Challenge dataset.

A gait recognition that analyses both shape and motion is proposed in [38]. The gait period here is depicted as ten phases. Spatiotemporal shape features are obtained from these phases in the form of Fourier descriptors. The silhouette contour at each step is segmented by fitting ellipses. The similarity is calculated utilising Bhattacharyya distance between the ellipse parameters taken as features. Dynamic time warping (DTW) is applied to compare leading knee rotation with relevance to arm swing pattern over a gait cycle. DTW is used so as to counteract the effects of walking speed, clothing, shadows, and hair styles.

4   Model-based techniques

While basic spatiotemporal methods give cues as to how the body position vary with accordance to time as a whole, it would be much more accurate to do a spatiotemporal analysis on all articulation points separately. The implementation of that sort will fall under the category of joint trajectory or model-based methods. That is, the trajectory of each joint is tracked live and analysed as individual components; efforts are made to model the human structure accurately.

Bulb markers can be attached to certain points on the body considered necessary for gait analysis such as ankles, knees, hands, elbows, shoulders and torso. When observed from a camera with a low exposure, only the bulb illumination can be perceived. This method facilitates an easier and a more accurate analysis of gait through computer vision. Rawesak T. & Bobick [37] implemented

this by strapping 18 human subjects with 16 markers at appropriate locations and projected their gait at a sagittal angle. The sensors were able to reconstruct a mobile skeletal structure recovered from the joints. From this data, they were able to assess the articulation points over time. The variance in time was normalised by applying DTW, and the recognition was based on the nearest neighbour algorithm to produce a modest recognition rate of 73%.

A study by Z. J. Geradts et al. [74] was conducted to be able to extract gait-related parameters from all three planes – frontal, transverse and sagittal – from surveillance cameras. 11 human subjects participated in the experiment and involved the use of 11 bulb markers fitted to the necessary points to each subject. They were able to observe various parameters from step length, cycle time and cadence to joint angles and spatial positioning. After a simple analysis of variance (ANOVA) on the gait parameters extracted, it seemed like the foot angle exhibited the most variance and then the time average hip joint angles followed by the step length. Hence these are considered to be the best parameters to be used for recognition. However, their research concluded that the gait analysis cannot be used for identification at that time (the year 2002).

Rawesak T. & Bobick later produced a study on the recognition of gait in different speeds of walking [75], but this time, they resorted to a more comfortable reflective suit for the articulation point signal extraction. The experimental is described in [79]. A 12-camera VICON MoCap system is used for the 3D motion analysis. The result based on 15 human subjects concluded that a positive linear correlation could be observed between cadence and speed, and a negative exponential correlation could be observed between stride time and speed.

The methods described so far require the use of complicated hardware for better accuracy. They either require reflectors, bulb markers, or magneto sensors to be fitted on to the points of interest of the human subject to gather the point-light information during his/her gait. Due to their nature, these methods are not practically feasible for biometric application. It is to note that the concept of being an 'unobtrusive' means of biometrics is lost here.

Not all model-based techniques, however, are impractical for application. Zhang et al. [32] show that it is possible to extract a five-link biped human model from a two-dimensional video feed to produce a model-based gait recognition system. The five links extracted consist of both the lower and upper leg portions and the upper body. The Metropolis-Hastings algorithm [80] was used for the feature extraction. The arm motion is neglected in this study. The changes in angular displacement of these links in the sagittal elevation angle (SEA) are analysed to using the HMM for the gait recognition. The method was applied to both CMU MoBo dataset as well as USF Gait Challenge video dataset.

An innovative yet simple method for locating the articulation points of the lower limb joints was implemented by M. Goffredo et al. [76]. By making smart estimates on where to initialise the points, the point-light data for the hip, both knees and ankles were extracted. This method was able to extract these points over multiple views as provided by the CASIA-B video database. By recording the temporal changes of these points, a profile recorded could be recognised with the help of the k-nearest neighbour algorithm (kNN).

A standard video feed would provide a two-dimensional data for processing. When added with depth based information, more accurate conclusions can be drawn to aid recognition. Microsoft Kinect provides this functionality. The Kinect is used in references [77] and [78] by facilitating three-dimensional data flow for a more natural and efficient biometric gait recognition.

Table 4: Datasets for Gait Analysis

Database	Year*	Env	View	Sub.	Seq.	Other variations
UCSD [40]	1998	FO	1	6	42	
MIT AI [81]	2001	FI	4	24	194	Time
CMU MoBo [82]	2001	TI	6	25	600	Speed(2), load(2), inclination(2)
HID Georgia Tech [83]	2001	FIO	3	20	>280	Time
HID-UMD Dataset 1 [84]	2001	FO	4	25	100	
HID-UMD Dataset 2 [84]	2001	FO	2	55	220	Time(2)
CASIA Dataset A [68]	2001	FO	3	20	240	
SOTON Small DB [3]	2002	FI	4	12	n/a	Load(4), clothing(3), footwear(6), speed(3)
SOTON Large DB [85]	2002	FTIO	2	114	2128	Terrain(3)
USF Gait Challenge [43]	2002	FO	2	122	1870	Terrain(2), footwear(2), load(2), time(2)
CASIA Dataset B [86]	2005	FI	11	124	13640	Clothing(2), load(2)
CASIA Dataset C [87]	2005	FO	1	153	612	Speed(3), load(2)
CASIA Dataset D [88]	2009	FI	1	88	880	
OU-ISIR Speed Transition [89]	2007	FTI	1	179	n/a	Speed shift
OU-ISIR Large Population [90]	2009	FI	2	4007	7842	
TUM-IITKGP [61]	2010	FI	2	35	840	Load(2), occlusion
OU-ISIR Inertial Sensor [91]	2011	FI		744	3468	Inclination(3)
SOTON Temporal [92]	2011	FI	12	25	26160	Time(5), clothing(2), footwear(2)
OU-ISIR Treadmill - A [93]	2012	TI	1	34	612	Speed(9)
OU-ISIR Treadmill - B [93]	2012	TI	1	68	2176	Clothing(32)
OU-ISIR Treadmill - C [93]	2012	TI	25	200	5000	
OU-ISIR Treadmill - D [93]	2012	TI	1	185	370	Gait fluctuations
TUM-GAID [51]	2012	Fi	1	305	3370	Load(2), footwear(2), time(2), clothing(2)

* The year indicates the year of recent release, not the year of its initial release. SOTON released its first version in 1996 and its first temporal set in 2003. OU-ISIR Treadmill datasets were iteratively developed from 2007-12.
Env Legends: F - static flooring, T - treadmill, I - indoor, O - outdoor.

5 Gait Datasets

With the outbreak of a substantial amount of algorithms to analyse gait there also comes a need to compare them. A standard gait dataset would be able to serve means so as to benchmark such algorithms especially in the case of biometric application. The categories of datasets cover a wide range based on the needs of the gait analyst from lightweight datasets to large-scale databases. An overview of the gait databases described here is given in Table 4.

When DARPA launched the HumanID programme in the year 2000, many institutions joined and released their first version of the database in the year 2001. Institutions that released their dataset for public usage include MIT, CMU, SOTON, Georgia Tech, UMD, USF, and CASIA. Nearly all of the institutions whose databases are described in this section are associated with this programme. The programme ended in 2004 due to privacy issues [3], but the databases compiled as a result is still publicly available from the institutions that developed them.

5.1 First Datasets on Gait

When gait analysis was increasing in interest as a biometric, the University of Southampton (SOTON) generated its gait dataset in the year 1996 [94]. It had only four subjects with a total of just 16 gait sequences. Self-occlusion occurs when the visual perception of one leg overlaps with that of the other leg. The first SOTON dataset attempted to reduce the self-occlusion problem by making the subjects wear white tracksuits with a single dark stripe vertically down either side walking frontoparallel with a plain cloth background. The visible line can help differentiate and track the leg closest to the camera throughout the gait cycle.

The first known dataset to become publicly available was developed by the Visual Computing Group in the University of California San Diego (UCSD) [3] in the year 1998. Its last update included six subjects and seven instances each adding up to a total of 42 frontoparallel sequences (sagittal observation) [40]. The number of subjects is still considerably small for a provable biometric application (for what it was intended). But the demands were met at its time, and its response paved way for other gait datasets to emerge.

MIT compiled a gait dataset with 24 persons at various trials taken at four different views in its Artificial Intelligence Laboratory [81]. With 194 gait sequences, it became one of the first multi-view gait datasets to be used in its time. Due to the arrival of many other large-scale datasets in about the same time, the usage of the MIT gait database became diminished in literature.

5.2 Carnegie Mellon University (CMU)

The CMU Motion of Body (MoBo) database was compiled in the Robotics Institute, Carnegie Mellon University. It is a treadmill based dataset, i.e., the gait sequences are recorded with the subjects walking on the treadmill. One gait instance, i, was taken for each of four gait variations recorded for 25 subjects, s taken at six viewpoints, v.

$$25s \times 4i \times 6v = 600 \text{ seq.}$$

14

The variations are slow walk, fast walk, incline walk, and walk with the ball [82]. The videos are recorded inside the lab (called the CMU 3D room). The CMU MoBo database was one of the first public databases released as part of the HumanID programme it easily became the first to be accessed by a wider range of people.

5.3   Georgia Institute of Technology

The dataset released by Georgia Tech, HID (Human ID), contains both video and motion capture data. There were a total of 20 subjects but were split in different ways according to the group of gait data collected. 15 members took part in the outdoor and outdoor video gait database accounting up to 268 gait instances. 18 members wore a magnetic sensor suit for motion capture compiling 20 gait instances wherein 2 of the subjects have additional motion capture data taken at different times. There are also bonus videos recorded as part of calibration which could also be used for gait analysis.

The outdoor data is collected from the terrace of the building while the indoor data is taken in lab conditions in front of a white wall and grey carpet. MoCap videos were recorded in a green room while the data itself is available in MAYA format. More detailed information on database description can be found in [83].

5.4   University of Maryland (UMD)

The gait database designed by the University of Maryland (UMD) has two datasets; the first one with multiple views and the second one with more subjects [84].

5.4.1   Dataset 1

The gait of 25 subjects, s, were observed in 4 different directions, v: frontal anterior, frontal posterior, frontoparallel left and frontoparallel right. The gait sequences were recorded outdoors in an environment that seems to resemble a courtyard. Thus the total sequence count becomes

$$25s \times 4v = 100 \text{ seq.}$$

5.4.2   Dataset 2

In an environment similar to that of the previous dataset, the gait of 55 subjects, s were recorded in two directions, v, while walking along a T-shaped pathway. The two views were orthogonal to each other and captured simultaneously. The dataset accounted two gait instances i for each subject which brings the sequence count to be

$$55s \times 2i \times 2v = 220 \text{ seq.}$$

5.5   University of Southampton (SOTON)

The HumanID programme caused SOTON to reformulate its dataset with more individuals and reduced clothing constraints. With 28 subjects and four sequences per subject, the size of the dataset came up to 112 sequences in the year 2001. This database was used in [21, 35, 43]. SOTON again revamped its database in the year 2002. The gait database was structured in two different datasets called the SOTON small and SOTON large.

5.5.1   Large Dataset

The larger dataset was designed with a combination of indoor and outdoor scenarios of 114 subjects [85]. The following are the different walking conditions covered:

- terrain   :   indoor flooring, indoor treadmill, outdoor asphalt
- direction   :   towards left of camera,
  towards right of camera
- viewpoint   :   normal, oblique

The indoor background is as same for the small database, but the outdoor background has vehicles and pedestrians moving across at a distance behind the subject being observed. The level of dynamic activity in the outdoor variation is intended to pose a natural challenge for computerised gait recognition. The total size of the dataset exceeds 350 GB. References [51, 95] report a total of 2128 gait sequences in this dataset.

5.5.2   Small Dataset

Though the large database had the most members, the small database with 12 subjects had the most covariates compared to all other currently available public databases. Gait sequences were recorded in different conditions as follows:

- load   :   handbag, barrel bag (in two poses), rucksack, no load
- clothing   :   raincoat, trenchcoat, casual
- footwear   :   flip-flops, bare feet, socks, boots, trainers, own shoes
- speed   :   slow, quick, normal speed
- direction   :   towards left of camera,
  towards right of camera
- viewpoint   :   normal oblique, normal elevated, frontal view

The background is staged with a green curtain and a dark green walkway. There is not yet a credible source to state exactly how many gait sequences are present in this database. It is also to note that not all 12 subjects perform all of the above variations; studies shows records of only 11 subjects [28, 45].

Table 5: SOTON Temporal Gait Sessions

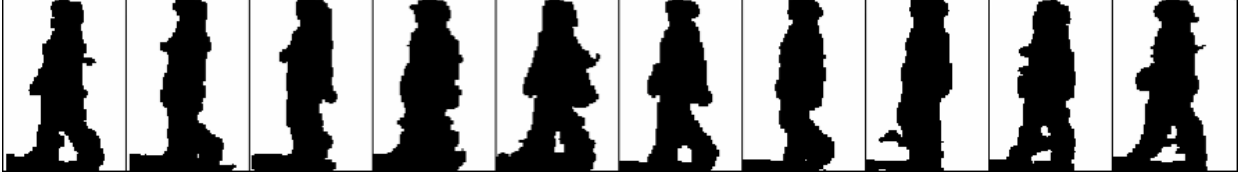| Session	Aug.	Sep.	Dec.	May	Aug
t	0	1	4	9	12
# Sub.	25	23	22	21	18

Figure 3: A sample sub-sequence of the silhouettes provided in the USF Gait Challenge database. This illustration contains one frame for every three frames in the sequence. Notice that the shadow produced by the subject is also captured leaving the heel angle incalculable for most of the sequences.

5.5.3 Temporal Dataset

The database consists of gait sequences from 25 subjects spanning over a period of a complete year taken at 5 (irregular) intervals. 12 cameras (v) capture the gait of each subject. The sessions were conducted as shown in Table5. 20 instances, i, were recorded for every subject for each session. Calculating with the above information, we obtain the total number of sequences

$$(25s + 23s + 22s + 21s + 18s) \times 20i \times 12v = 26160 \text{ seq.}$$

The observation was done in the Multi-Biometric Tunnel of the University of Southampton [96]. The background is tiled with red, green and blue squares. This facilitates feature mapping to consolidate the camera views to construct a 3-D image of anything that passes through the tunnel. There were also slight specific variations in clothing and footwear. Details of which are provided in [92]. This gait database is clearly the largest to cover the temporal aspect of gait to date.

5.6 University of South Florida (USF)

The HumanID Gait Challenge dataset was compiled by the Computer Vision and Pattern Recognition Group, University of South Florida (USF). It was the first dataset to become immediately popular after the start of the DARPA's HumanID programme. 122 subjects had their gait sequences recorded in the following different conditions:

- shoe type   :   A, B
- load   :   with suitcase, without suitcase
- terrain   :   grass, concrete
- time   :   May 2001, Nov 2001
- viewpoint   :   sagittal left, sagittal right

All of the above come together to make 32 possible combinations, but not all of them are applied to each of the subjects resulting in 1870 sequences. The bulk of video data adds up to 1.2 terabytes [97]. One must follow a complicated and time-consuming process to get access to this video dataset, but USF provides free access to the silhouettes of the videos processed using the Gait Baseline algorithm [43]. A sample sub-sequence of the silhouettes is shown in Figure 3 This silhouette dataset is what is used by most of the published literature that utilises the USF Gait Challenge dataset [23–25, 31, 48, 69–71]. Even the famous GEI algorithm [4] used not the video, but only the silhouette database of the USF.

The foot angle was found to have the most variance among other primitive gait measures [74]. This fact is astounding since the foot angle is a highly sensitive feature that would be difficult to be measured with an acceptable accuracy through the silhouette based methods. The extraction of this feature would become nearly impossible with the silhouette data readily available as part of the USF Gait Challenge dataset. This is because most of the silhouettes in this dataset is produced in such a way have the foot occluded with shadows in which the boundary between the two is not well defined.

5.7 Institute of Automation, Chinese Academy of Sciences (CASIA)

CASIA has developed four public gait databases till date. The development started in 2001 at the National Laboratory of Pattern Recognition (NLPR). In addition to the video, the silhouettes for each of the following datasets are freely available for download.

5.7.1 Dataset A

This dataset was previously known as the NLPR Gait Database, early literature such as [68] and [87] use this name. CASIA-A is a basic gait dataset with the gait of 20 subjects, s, recorded at 3 views, v. 4 instances, i, were recorded for each subject leading to sequence count of

$$20s \times 4i \times 3v = 240 \text{ seq.}$$

The three views – sagittal, 45° and 90° – are captured simultaneously in an outdoor environment (in front of a building).

5.7.2 Dataset B

With 124 individuals (s) each performing 10 gait instances (i) observed in 11 simultaneous angles, the total number of sequences for the CASIA-B dataset would be

$$124s \times 10i \times 11v = 13640 \text{ seq.}$$

The ten instances can be split up as

- 6 normal instances

- 2 instances wearing a coat

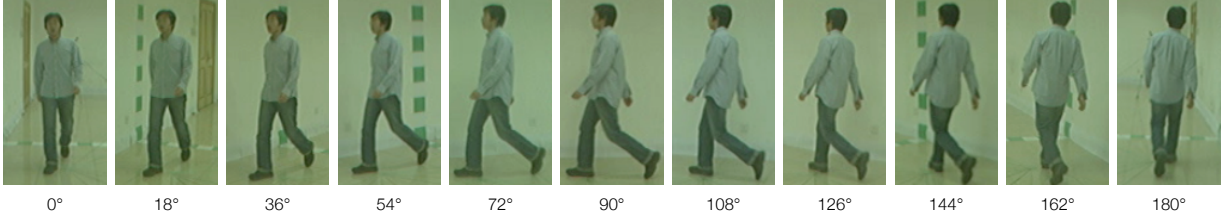| 0° | 18° | 36° | 54° | 72° | 90° | 108° | 126° | 144° | 162° | 180° |

Figure 4: Cropped frames from CASIA Dataset B. A frame is taken from each of the 11 angles for a single individual at the same time.

- 2 instances carrying a bag

Along with an additional video of bare background, the total number of videos actually becomes 15004 (approximately 17.4 GB). The background is mostly plain light green with two stage markings covering both the wall and the floor [86]. This is the most common multiview database in literature. Figure 4 shows a depiction of the dataset for a given time instant from each of the 11 angles.

5.7.3 Dataset C

The gait sequences of 153 subjects, s, were collected. Each subject performed 4 gait instances in different conditions, c: slow walk, normal walk, fast walk, and walk while carrying a bag [87]. Unlike CASIA-A and CASIA-B, this dataset is only observed at a single sagittal angle. Hence the total number of gait sequences becomes

$$153s \times 4c = 612 \text{ seq.}$$

The sequences were recorded outdoors at night using an infrared camera.

5.7.4 Dataset D

This dataset of synchronised footprint scans and gait images of 88 subjects. The camera observed the user from a sagittal angle while the Rscan Footscan scans the foot placement with an equal sampling rate while the subject progresses through the gait cycle. 10 trials are taken per subject on average resulting in a total of around 880 sequences. CASIA also hosts a MATLAB mat file that contains the data and can be freely downloaded from its site.

5.8 Osaka University – Institute of Scientific and Industrial Research (OU-ISIR)

The OU-ISIR produced a whole range of biometric databases. The ones that directly correspond to gait analysis are provided in this section. The treadmill datasets were prepared over a long course of time (from 2007 to 2012). The information for all treadmill datasets can be obtained from [93]. Only the size-normalised silhouettes will be publicly available, not the videos themselves, leaving the background irrelevant for our discussion.

Table 6: Clothing styles in OU-ISIR-B Dataset [93]		
RP: Regular Pants	BP: Baggy Pants	SP: Short Pants
Sk: Skirt	CP: Casual Pants	HS: Half Shirt
FS: Full Shirt	LC: Long Coat	Pk: Parker
DJ : Down Jacket	CW: Casual Wear	RC: Rain Coat
Ht: Hat	Cs: Casquette Cap	Mf: Muffler

5.8.1 Treadmill dataset A – Speed Variation

34 subjects, s, walk on a treadmill with the speed periodically increasing from 2 km/h to 10 km/h at intervals of 1 km/h. Hence 9 different speed variations, c, are accounted at a sagittal angle. This process is repeated twice having two instances, i, of each variation. This results in the number of gait sequences as

$$34s \times 9c \times 2i = 612 \text{ seq.}$$

5.8.2 Treadmill dataset B – Clothing Variation

This consists of 68 subjects, s, with 32 combinations of clothing styles, c, recorded along a sagittal angle resulting in a total sequence count of

$$68s \times 32c = 2176 \text{ seq.}$$

The various clothing styles are as listed in Table 6.

5.8.3 Treadmill dataset C – View Variation

200 subjects are recorded in 25 different points of view synchronously accounting for 5000 gait sequences in total. The dataset also covers a substantial variation of age group from 4 to 75 years old. Male and female subjects are equally distributed. This dataset would hence facilitate age group and gender detection (soft biometric) rather than gait recognition as only one instance is supplied per subject.

Apart from its description, the OU-ISIR treadmill dataset C is still not released publicly. On the time of writing this paper, the dataset is still under preparation.

5.8.4 Treadmill dataset D – Gait fluctuations

The features of a gait cycle, in general, would not be the same in every period of an individual's gait. A certain amount of fluctuation can be observed. This dataset aims to measure this fluctuation with the aim to use this feature as a biometric attribute. 185 subjects, s, were recorded at the sagittal angle to measure fluctuations that could occur in multiple gait periods. Each member had two trials, i resulting in a number of sequences of

$$185s \times 2i = 370 \text{ seq.}$$

Gait fluctuations are measured in terms of Normalised AutoCorrelation (NAC) [93]. The subjects were grouped into that with higher NAC (least fluctuating), DB_{high} and that of lower NAC (most fluctuating), DB_{low}. There were 100 members in each group, and 4 trials were made for each, but 15 subjects were part of both groups.

5.8.5 Large Population Dataset

This dataset consists of gait silhouettes of over 4000 subjects with ages of 1 to 94 years. The gait sequences were captured with two cameras at two different angles out of which only one is available so far as part of the publicly available dataset. This is the gait dataset that involves the largest number of human subjects till date. The total number of gait sequences in this dataset is reported to be 7842 [51, 95]. A detailed description of this dataset can be found in [90].

5.8.6 Speed Transition Dataset

While all other datasets concentrated on keeping the speed relatively constant for a given gait sequence, this dataset aims to observe the gait while allowing changes in speed within a single gait sequence. This is separated into of two datasets. In dataset 1, 179 subjects are made to walk towards a wall from a given point while exhibiting gradual decrease in walking speed. While dataset 1 was recorded indoors on flat ground, dataset 2 was treadmill-based. Dataset 2 consisted of gait sequences from 178 subjects. Each gait sequence included either of acceleration or deceleration of walking speed between 1 km/h to 5 km/h. Both datasets have a gallery set which includes the subjects walking at a constant speed of 4 km/h [89].

There aren't much reported research that concerns the use of this particular dataset which could be due to the level of challenge to be faced by algorithms to recognise gait in such constraints. The rare use of this database could also be due to the extent of artificial constraints applied to the subjects. The subjects have to control their gait effectively to be conscious about the speed transition. This anticipation could inhibit their natural gait.

5.8.7 Inertial Sensor Dataset

Unlike the other datasets, this one includes the kinetic data from gait. The apparatus is in the form of a belt that has three IMUZ sensors and a smartphone attached. Each IMUZ sensor consists of a triaxial accelerometer and a gyroscope. The subject wears the belt around the waist as he/she walks through the specified track. It is claimed to be the largest ever inertial sensor-based gait dataset [91]. The dataset is split into two subsets. The first subset has 744 subjects with two trials of flat-ground gait. The second subset is of 495 subjects two trials for no inclination, one for up-slope walk and another for down-slope walk. Thus an estimate of the total number of gait sequences would come across

$$(744s \times 2i) + (495s \times 4i) = 3468 \text{ seq.}$$

Figure 5: A sample from the TUM-GAID database with a frame taken from each of the 3 conditions taken at both January session (first three) and April session (last three). The bottom set of images correspond to the respective depth image at the same instant.

5.9   Technical University of Munich (TUM)

5.9.1   TUM-IITKGP

The joint research efforts of the TUM and the Indian Institute of Technology Kharagpur (IIT-KGP) has brought forth a gait database which has become the first to address the problem of occlusion in gait recognition [61]. Each of the 35 subjects, s, followed 6 different walking conditions, c, two trials each for left to right and right to left directions. Hence 4 instances are recorded for each of the configuration per subject. The total number of gait sequences becomes

$$35s \times 6c \times 4i = 840 \text{ seq.}$$

The configurations are regular, hands in pocket, wearing a backpack, wearing a gown, dynamic occlusion, and static occlusion. Dynamic occlusion refers to the scenario when the subject under observation is occluded by a moving object. In this case, dynamic object relates to another individual moving in the opposite direction and parallel to the subject. Static occlusion is the scenario where the subject is temporarily occluded by an object that doesn't move. The static object in here refers to another individual standing in front of the camera so as to block a portion of the gait sequence capture.

5.9.2   TUM-GAID

This is a database that was created with an intention to recognise gait from audio, image and depth (GAID) information (Figure 5). The gait data was compiled from 305 subjects in three walking conditions (normal, backpack, coating shoes). While the image and depth data have been studied before, the audio data would facilitate acoustic gait recognition [51]. The variation in the dataset is as given below.

- load   :   with backpack (~ 5 kg),
                  without backpack
- footwear   :   regular shoes, coating shoes
- clothing   :   winter attire, casual attire
- time   :   Session 1 (January 2012),
                  Session 2 (April 2012)

176 subjects were recorded in the January session (at -15°C) and 161 subjects in the April session (at 15°C).

There were five trials in each subject per session. Each trial consists of walking once towards the right of the camera and another towards the left. Three trials were recorded for normal walk, one trial while wearing coating shoes over their own shoes, and one trial while wearing a backpack. The total number of sequences can be calculated as

$$(176s + 161s) \times 5c \times 2i = 3370 \text{ seq.}$$

The different clothing conditions are also associated with the weather of the sessions. Subjects wore heavier winter clothing in the first session while a more casual clothing in the second session. 32 of the subjects were common in both sessions. Hence the data from these members can be used for analysing the variations in gait with respect to the differences in clothing and time.

5.10   Other Gait Datasets

Recent publications show proposals of datasets that are not as prevalent in use as the ones illustrated in Table 4.

Jordan Frank compiled an accelerometer-based gait dataset in McGill University in July 2010 [98]. It is freely available for download without the need of a license. The data was obtained from mobile phones carried by the subjects and is extracted using an open-source Android app called HumanSense. The dataset contains the triaxial accelerometer readings for 20 subjects. Each gait sequence is a 15-minute walk. Gait sequences of each individual were captured in two sessions taken at different days. The dataset also includes the gender, height, weight, clothing and shoe descriptions of each subject. Frank show how this data can be used for both activity recognition and gait recognition in [99].

The Multimedia University, Malaysia (MMU) developed a gait database known as MMUGait DB [100]. The database can be split into two sets, MMUGait Large DB with 82 subjects, and MMUGait Gait Covariate DB with 19 subjects. Each instance is recorded from the side view and oblique view. The MMUGait Large DB contains at least 20 gait sequences per subject in both towards left and right directions. The MMUGait Covariate DB consist of 10 sequences for each of the 11 covariates. These include three types of clothing, four types of load, two walking speeds, and two types of footwear. Their database, however, is not publicly accessible.

A team lead by Kastaniotis in the University of Patras Computer Vision Group (UPCV) compiled a Kinect-based gait dataset called UPCVgait. As the data is recorded with a Microsoft Kinect and it includes both depth information as well as RGB videos. 5 gait sequences were captured for each

of the 30 subjects. It was first used in [101] for gender and pose estimation. It was also used in [78] for gait recognition. This dataset is only available at [102].

6   Discussion

Ever since the time of its introduction, gait analysis was largely of medical relevance. It was only at the break of the 21st century did gait analysis also become of increasing interest outside the clinic and into forensic science. The human body is designed to walk in a way such that the energy that is expended is kept to a minimum. The dissipation of energy is dependent on various factors such as the biological structure, load exerted, and the experience of the individual. These differences make the natural gait of each person to be distinct. This distinction is what analysts try to capture as gait biometrics.

Biometric gait recognition is yet to reach its peak accuracy. The state of the art published literature shows groundbreaking results. Nevertheless, they have been produced with datasets that are imposed by serious constraints. Even with the complete description of the USF Gait Challenge, papers show conflicting results with the same set of algorithms. A thorough, unbiased, practical evaluation of the recent methods is much of need at this time. This assessment should also cover validation through more than a single dataset. It is also questionable whether the true natural gait of each subject is captured in the popular gait datasets. During the start of the walk, an individual would have adequate control over his/her gait. The currently available datasets do not always take this issue into account. Though datasets have attempted to account for the inhibiting factors of gait, there is still the problem of internal and external control that one can exhibit in his/her gait.

There was a study which took place at the end of the 20th century which compares the performance of 3D camera systems available at that time [103]. However, the technology has evolved and many new techniques have arrived today leaving the results obsolete. Hence a similar study remains yet to be compared to evaluate the performance of the state of the art MoCap systems.

7   Research Directions

Gait analysis is an interesting study and is proven to be applicable for diverse domains of applications. There are many open areas of research from which one can choose in the field. We have segregated them into two groups – active areas and those that are least explored.

7.1   Active areas

- *Reliable recognition independent of clothing style.* Several algorithms have been outlined to combat this problem (e.g., [53, 86]) and a handful of datasets to help with this regard (CASIA-B, OU-ISIR-B, TUM-GAID, and so on). However, state of the art gait biometrics algorithms do suffer a significant depreciation when the clothing style changes.

- *Gait recognition at different walking speed.* With datasets like CASIA-C and OU-ISIR-A, gait recognition at different speeds is becoming more of interest [75, 79, 104]. There are,

however, further improvements that can be made.

- *View-independent gait recognition.* Numerous studies that propose recognition models that could cope with multiple views. Many of which can be observed in Tables 1, 2 and 3. Steady progress is still being made in this area.

- *A comparative study between model-based and model-free recognition methods.* Though studies contrast on the merits and demerits of both approaches, there is still space for an in-depth comparative analysis with newer technology such as the upgraded versions of Kinect.

- *Unbiased comparison of state of the art gait recognition.* Many of the studies discussed in this paper report conflicting results of correct classification rates when performances of established algorithms are compared, even with the same dataset. The existing algorithms are to be compared with multiple datasets and without bias.

- *Gait reidentification performance.* Gait identification with occlusion can be a challenge by itself wherein multiple cycles are provided for training per person. However, identifying whether two given gait signatures are from the same person can be even more difficult especially when considering multiple views.

7.2   Least explored

- *Characteristic differences in gait based on ethnicity.* People from different regions do have a characteristic gait. CASIA datasets are composed of Chinese individuals, while the USF gait dataset are largely American. More datasets are to be created across various ethnicity to study the associated differences between them in terms of their gait.

- *Ranking of factors that inhibit gait.* The confounding factors of gait are as listed in section 2. Though known, they are not compared in a way that would determine to which extent they inhibit gait. For instance, to what instance could training affect biometric gait? This has been an open question to which no authoritative reports are currently available.

- *Different machine learning methods for gait recognition.* The novelty of the recognition algorithms lies on the technique in which features are extracted. Commonly used classifiers are ANN, kNN, and SVM. A detailed analysis on how different classifiers effect the prediction rate through state of the art gait feature extraction algorithms is yet to be reported.

8   Conclusion and Future Work

There is no doubt that gait analysis is still a growing field with a whole range of applicable areas. Ever since its boom in the second millennium, it has captured so much attention from different domains. It is of keen interest in modern medicine, security agencies, military organisations, sports industry, bionic prosthetics, and social analytics. So much progress has been made through time, and it will continue to do so in the future.

This survey covered numerous papers published in gait literature with a particular focus on gait biometrics. Our objective in the near future is to do an empirical study on all existing gait templates

and address at least two of the unexplored research areas: comparison of various machine learning classifiers on gait features and ranking the factors that inhibit gait.

References

[1] M. W. Whittle, *Gait Analysis: An Introduction*, 4th ed.   Butterworth-Heinemann, 2007.

[2] J. E. Boyd and J. J. Little, "Biometric gait recognition," in *Advanced Studies in Biometrics*. Springer, 2005, pp. 19–42.

[3] M. S. Nixon, T. Tan, and R. Chellappa, *Human identification based on gait*.   Springer Science & Business Media, 2010, vol. 4.

[4] J. Han and B. Bhanu, "Individual recognition using gait energy image," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 2, pp. 316–322, 2006.

[5] J. C. Menant, J. R. Steele, H. B. Menz, B. J. Munro, and S. R. Lord, "Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people," *Gait & posture*, vol. 29, no. 3, pp. 392–397, 2009.

[6] H. B. Menz, S. R. Lord, and R. C. Fitzpatrick, "Acceleration patterns of the head and pelvis when walking on level and irregular surfaces," *Gait & posture*, vol. 18, no. 1, pp. 35–46, 2003.

[7] A. F. R. Kleiner, M. Galli, A. A. do Carmo, and R. M. Barros, "Effects of flooring on required coefficient of friction: Elderly adult vs. middle-aged adult barefoot gait," *Applied Ergonomics*, vol. 50, pp. 147–152, 2015.

[8] R. Cham and M. S. Redfern, "Changes in gait when anticipating slippery floors," *Gait & posture*, vol. 15, no. 2, pp. 159–171, 2002.

[9] H.-L. Chien, T.-W. Lu, and M.-W. Liu, "Effects of long-term wearing of high-heeled shoes on the control of the body's center of mass motion in relation to the center of pressure during walking," *Gait & Posture*, vol. 39, no. 4, pp. 1045 – 1050, 2014.

[10] S. Franklin, M. J. Grey, N. Heneghan, L. Bowen, and F.-X. Li, "Barefoot vs common footwear: a systematic review of the kinematic, kinetic and muscle activity differences during walking," *Gait & posture*, vol. 42, no. 3, pp. 230–239, 2015.

[11] R. Wang, "Biomechanical consequences of gait impairment at the ankle and foot: Injury, malalignment, and co-contraction," Ph.D. dissertation, KTH Royal Institute of Technology, 2012.

[12] H.-J. Lee and L.-S. Chou, "Detection of gait instability using the center of mass and center of pressure inclination angles," *Archives of Physical Medicine and Rehabilitation*, vol. 87, no. 4, pp. 569–575, 2006.

[13] C. Beaudart, J.-Y. Reginster, J.-L. Croisier, J. Slomian, F. Buckinx, M. Locquet, A. Quabron, and O. Bruyère, "Correlation between muscle mass and muscle strength and their association with physical performance and gait speed," *Osteoporosis International*, vol. 26, no. S1, p. S49, 2015.

[14] M. F. Vieira, G. S. d. S. e Souza, G. C. Lehnen, F. B. Rodrigues, and A. O. Andrade, "Effects of general fatigue induced by incremental maximal exercise test on gait stability and variability of healthy young subjects," *Journal of Electromyography and Kinesiology*, vol. 30, pp. 161–167, 2016.

[15] A. M. Putnam, "The effects of an exhaustive treadmill protocol on running gait in army reserve officer training corps cadets," Ph.D. dissertation, Honolulu: University of Hawaii at Manoa, 2013.

[16] J. M. Montepare, S. B. Goldstein, and A. Clausen, "The identification of emotions from gait information," *Journal of Nonverbal Behavior*, vol. 11, no. 1, pp. 33–42, 1987.

[17] V. Moniz-Pereira, S. Cabral, F. Carnide, and A. P. Veloso, "Gait analysis in the elderly: an induced acceleration approach," *Journal of Biomechanics*, vol. 45, Supplement 1, p. S229, 2012, proceedings of {ESB2012} - 18th Congress of the European Society of Biomechanics.

[18] M. P. Castro, M. C. Figueiredo, S. Abreu, H. Sousa, L. Machado, R. Santos, and J. P. Vilas-Boas, "The influence of gait cadence on the ground reaction forces and plantar pressures during load carriage of young adults," *Applied Ergonomics*, vol. 49, pp. 41 – 46, 2015.

[19] C. Mummolo, S. Park, L. Mangialardi, and J. H. Kim, "Computational evaluation of load carriage effects on gait balance stability," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 19, no. 11, pp. 1127–1136, 2016.

[20] E.-J. Hyung, H.-O. Lee, and Y.-J. Kwon, "Influence of load and carrying method on gait, specifically pelvic movement," *Journal of Physical Therapy Science*, vol. 28, no. 7, pp. 2059–2062, 2016.

[21] J. B. Hayfron-Acquah, M. S. Nixon, and J. N. Carter, "Automatic gait recognition by symmetry analysis," *Pattern Recognition Letters*, vol. 24, no. 13, pp. 2175–2183, 2003, audio- and Video-based Biometric Person Authentication (AVBPA 2001).

[22] S. A. Niyogi and E. H. Adelson, "Analyzing and recognizing walking figures in xyt," in *1994 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. IEEE, 1994, pp. 469–474.

[23] T. H. Lam, R. S. Lee, and D. Zhang, "Human gait recognition by the fusion of motion and static spatio-temporal templates," *Pattern Recognition*, vol. 40, no. 9, pp. 2563 – 2573, 2007.

[24] X. Yang, Y. Zhou, T. Zhang, G. Shu, and J. Y. 0002, "Gait recognition based on dynamic region analysis." *Signal Processing*, vol. 88, no. 9, pp. 2350–2356, 2008.

[25] T. H. Lam, K. H. Cheung, and J. N. Liu, "Gait flow image: A silhouette-based gait representation for human identification," *Pattern recognition*, vol. 44, no. 4, pp. 973–987, 2011.

[26] C. P. Lee, A. W. Tan, and S. C. Tan, "Gait recognition with transient binary patterns," *Journal of Visual Communication and Image Representation*, vol. 33, pp. 69–77, 2015.

[27] X. Xing, K. Wang, T. Yan, and Z. Lv, "Complete canonical correlation analysis with application to multi-view gait recognition," *Pattern Recognition*, vol. 50, pp. 327–335, 2015.

[28] P. Arora, M. Hanmandlu, and S. Srivastava, "Gait based authentication using gait information image features," *Pattern Recognition Letters*, vol. 68, Special Issue on Soft Biometrics, pp. 336–342, 2015.

[29] Z. Liu and S. Sarkar, "Outdoor recognition at a distance by fusing gait and face," *Image and Vision Computing*, vol. 25, no. 6, pp. 817 – 832, 2007.

[30] A. Kale, N. Cuntoor, and R. Chellappa, "A framework for activity-specific human identification," in *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, vol. 4.   IEEE, 2002, pp. IV–3660 – IV–3663.

[31] Z. Liu and S. Sarkar, "Improved gait recognition by gait dynamics normalization," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 6, pp. 863–876, 2006.

[32] R. Zhang, C. Vogler, and D. Metaxas, "Human gait recognition at sagittal plane," *Image and Vision Computing*, vol. 25, no. 3, pp. 321 – 330, 2007, articulated and Non-rigid motion.

[33] T.-N. Nguyen, H.-H. Huynh, and J. Meunier, "Extracting silhouette-based characteristics for human gait analysis using one camera," in *Proceedings of the Fifth Symposium on Information and Communication Technology*, ser. SoICT '14.   New York, NY, USA: ACM, 2014, pp. 171–177.

[34] P. Huang, C. Harris, and M. Nixon, "Recognising humans by gait via parametric canonical space," *Artificial Intelligence in Engineering*, vol. 13, no. 4, pp. 359 – 366, 1999.

[35] J. P. Foster, M. S. Nixon, and A. Prügel-Bennett, "Automatic gait recognition using area-based metrics," *Pattern Recognition Letters*, vol. 24, no. 14, pp. 2489–2497, 2003.

[36] H. Murase and R. Sakai, "Moving object recognition in eigenspace representation: gait analysis and lip reading," *Pattern Recognition Letters*, vol. 17, no. 2, pp. 155 – 162, 1996.

[37] R. Tanawongsuwan and A. Bobick, "Gait recognition from time-normalized joint-angle trajectories in the walking plane," in *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2001.*, vol. 2.   IEEE, 2001, pp. II–726.

[38] S. D. Choudhury and T. Tjahjadi, "Gait recognition based on shape and motion analysis of silhouette contours." *Computer Vision and Image Understanding*, vol. 117, no. 12, pp. 1770–1785, 2013.

[39] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *International Journal of Computer Vision*, vol. 1, no. 4, pp. 321–331, 1988.

[40] J. Little and J. Boyd, "Recognizing people by their gait: the shape of motion," *Videre: Journal of Computer Vision Research*, vol. 1, no. 2, pp. 1–32, 1998.

[41] A. Y. Johnson and A. F. Bobick, "A multi-view method for gait recognition using static body parameters," in *International Conference on Audio-and Video-Based Biometric Person Authentication*. Springer, 2001, pp. 301–311.

[42] L. Wang, T. Tan, W. Hu, and H. Ning, "Automatic gait recognition based on statistical shape analysis," *IEEE Transactions on Image Processing*, vol. 12, no. 9, pp. 1120–1131, 2003.

[43] S. Sarkar, P. J. Phillips, Z. Liu, I. R. Vega, P. Grother, and K. W. Bowyer, "The HumanID gait challenge problem: data sets, performance, and analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 2, pp. 162–177, 2005.

[44] W. Kusakunniran, Q. Wu, H. Li, and J. Zhang, "Automatic gait recognition using weighted binary pattern on video," in *Sixth IEEE International Conference on Advanced Video and Signal Based Surveillance, AVSS'09*. IEEE, 2009, pp. 49–54.

[45] K. Bashir, T. Xiang, and S. Gong, "Gait recognition without subject cooperation," *Pattern Recognition Letters*, vol. 31, no. 13, pp. 2052–2060, 2010.

[46] E. Zhang, Y. Zhao, and W. Xiong, "Active energy image plus 2dlpp for gait recognition," *Signal Processing*, vol. 90, no. 7, pp. 2295–2302, 2010.

[47] S. Zheng, J. Zhang, K. Huang, R. He, and T. Tan, "Robust view transformation model for gait recognition," in *2011 18th IEEE International Conference on Image Processing*. IEEE, 2011, pp. 2073–2076.

[48] C. Wang, J. Zhang, L. Wang, J. Pu, and X. Yuan, "Human identification using temporal information preserving gait template," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 11, pp. 2164–2176, 2012.

[49] N. Liu, J. Lu, G. Yang, and Y.-P. Tan, "Robust gait recognition via discriminative set matching," *Journal of Visual Communication and Image Representation*, vol. 24, no. 4, pp. 439–447, 2013.

[50] Y. Dupuis, X. Savatier, and P. Vasseur, "Feature subset selection applied to model-free gait recognition," *Image and vision computing*, vol. 31, no. 8, pp. 580–591, 2013.

[51] M. Hofmann, J. Geiger, S. Bachmann, B. Schuller, and G. Rigoll, "The TUM gait from audio, image and depth (gaid) database: Multimodal recognition of subjects and traits," *Journal of Visual Communication and Image Representation*, vol. 25, no. 1, pp. 195 – 206, 2014, visual Understanding and Applications with RGB-D Cameras.

[52] M. R. Aqmar, Y. Fujihara, Y. Makihara, and Y. Yagi, "Gait recognition by fluctuations," *Computer Vision and Image Understanding*, vol. 126, pp. 38–52, 2014.

[53] P. Yogarajah, P. Chaurasia, J. Condell, and G. Prasad, "Enhancing gait based person identification using joint sparsity model and -norm minimization," *Information Sciences*, vol. 308, pp. 3–22, 2015.

[54] S. D. Choudhury and T. Tjahjadi, "Robust view-invariant multiscale gait recognition," *Pattern Recognition*, vol. 48, no. 3, pp. 798–811, 2015.

[55] X. Zhao, Y. Jiang, T. Stathaki, and H. Zhang, "Gait recognition method for arbitrary straight walking paths using appearance conversion machine," *Neurocomputing*, vol. 173, p. 530, 540 2016.

[56] I. Rida, X. Jiang, and G. L. Marcialis, "Human body part selection by group lasso of motion for model-free gait recognition," *IEEE Signal Processing Letters*, vol. 23, no. 1, pp. 154–158, 2016.

[57] K. Shiraga, Y. Makihara, D. Muramatsu, T. Echigo, and Y. Yagi, "Geinet: View-invariant gait recognition using a convolutional neural network," in *Biometrics (ICB), 2016 International Conference on*.   IEEE, 2016, pp. 1–8.

[58] C. Li, X. Min, S. Sun, W. Lin, and Z. Tang, "Deepgait: A learning deep convolutional representation for view-invariant gait recognition using joint bayesian," *Applied Sciences*, vol. 7, no. 3, p. 210, 2017.

[59] Z. Wu, Y. Huang, L. Wang, X. Wang, and T. Tan, "A comprehensive study on cross-view gait based human identification with deep cnns," *IEEE transactions on pattern analysis and machine intelligence*, vol. 39, no. 2, pp. 209–226, 2017.

[60] N. Cuntoor, A. Kale, and R. Chellappa, "Combining multiple evidences for gait recognition," in *Proceedings of the 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 3.   IEEE, 2003, pp. III–33 – III–36.

[61] M. Hofmann, S. Sural, and G. Rigoll, "Gait recognition in the presence of occlusion: A new dataset and baseline algorithms," in *WSCG '2011: Communication Papers, The 19th International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision*.   Václav Skala-UNION Agency, 2011, pp. 99–104.

[62] M. A. R. Ahad, *Motion history images for action recognition and understanding*.   Springer Science & Business Media, 2012.

[63] M. Hofmann, S. Bachmann, and G. Rigoll, "2.5D gait biometrics using the depth gradient histogram energy image," in *Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS)*.   IEEE, 2012, pp. 399–403.

[64] M. Hanmandlu and A. Das, "Content-based image retrieval by information theoretic measure," *Defence Science Journal*, vol. 61, no. 5, pp. 415–430, 2011.

[65] C. E. Shannon, "A mathematical theory of communication," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 5, no. 1, pp. 3–55, 2001.

[66] Z. Liu, Z. Zhang, Q. Wu, and Y. Wang, "Enhancing person re-identification by integrating gait biometric," *Neurocomputing*, vol. 168, pp. 1144–1156, 2015.

[67] R. R. Wang and T. Huang, "A framework of joint object tracking and event detection," *Pattern analysis and applications*, vol. 7, no. 4, pp. 343–355, 2004.

[68] L. Wang, T. Tan, H. Ning, and W. Hu, "Silhouette analysis-based gait recognition for human identification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, pp. 1505–1518, 2003.

[69] A. Kale, A. Sundaresan, A. Rajagopalan, N. P. Cuntoor, A. K. Roy-Chowdhury, V. Kruger, and R. Chellappa, "Identification of humans using gait," *IEEE Transactions on Image Processing*, vol. 13, no. 9, pp. 1163–1173, 2004.

[70] N. V. Boulgouris, K. N. Plataniotis, and D. Hatzinakos, "Gait recognition using linear time normalization," *Pattern Recognition*, vol. 39, no. 5, pp. 969 – 979, 2006.

[71] N. V. Boulgouris and Z. X. Chi, "Human gait recognition based on matching of body components," *Pattern Recognition*, vol. 40, no. 6, pp. 1763 – 1770, 2007.

[72] W. Zeng and C. Wang, "View-invariant gait recognition via deterministic learning," *Neurocomputing*, vol. 175, pp. 324–335, 2016.

[73] D. Muramatsu, Y. Makihara, and Y. Yagi, "View transformation model incorporating quality measures for cross-view gait recognition," *IEEE Transactions on Cybernetics*, vol. 46, no. 7, pp. 1602–1615, 2016.

[74] Z. J. Geradts, M. Merlijn, G. de Groot, and J. Bijhold, "Use of gait parameters of persons in video surveillance systems," in *AeroSense 2002*. International Society for Optics and Photonics, 2002, pp. 16–24.

[75] R. Tanawongsuwan and A. Bobick, "Performance analysis of time-distance gait parameters under different speeds," in *International Conference on Audio-and Video-Based Biometric Person Authentication*. Springer, 2003, pp. 715–724.

[76] M. Goffredo, I. Bouchrika, J. N. Carter, and M. S. Nixon, "Performance analysis for gait in camera networks," in *Proceedings of the 1st ACM Workshop on Analysis and Retrieval of Events/Actions and Workflows in Video Streams*, ser. AREA '08. New York, NY, USA: ACM, 2008, pp. 73–80.

[77] P. Chattopadhyay, S. Sural, and J. Mukherjee, "Frontal gait recognition from occluded scenes," *Pattern Recognition Letters*, vol. 63, pp. 9–15, 2015.

[78] D. Kastaniotis, I. Theodorakopoulos, C. Theoharatos, G. Economou, and S. Fotopoulos, "A framework for gait-based recognition using kinect," *Pattern Recognition Letters*, vol. 68, no. 2, pp. 327–335, 2015.

[79] R. Tanawongsuwan and A. Bobick, "A study of human gaits across different speeds," Georgia Tech, Tech. Rep, Tech. Rep., 2003.

[80] S. Chib and E. Greenberg, "Understanding the metropolis-hastings algorithm," *The American Statistician*, vol. 49, no. 4, pp. 327–335, 1995.

[81] L. Lee, "Gait analysis for classification," Artificial Intelligence Laboratory, Massachusetts Instutute of Technology, Cambridge, USA, Tech. Rep., 2002.

[82] R. Gross and J. Shi, "The cmu motion of body (mobo) database," Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RI-TR-01-18, June 2001.

[83] Georgia Tech – GVU Center, "Human identification at a distance," 2003. [Online]. Available: http://www.cc.gatech.edu/cpl/projects/hid/index.html

[84] University of Mariland, "Human identification at a distance, umd database," 2001. [Online]. Available: http://www.umiacs.umd.edu/labs/pirl/hid/data.html

[85] J. D. Shutler, M. G. Grant, M. S. Nixon, and J. N. Carter, "On a large sequence-based human gait database," in *Applications and Science in Soft Computing*.   Springer, 2004, pp. 339–346.

[86] S. Yu, D. Tan, and T. Tan, "A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition," in *18th International Conference on Pattern Recognition (ICPR'06)*, vol. 4.   IEEE, 2006, pp. 441–444.

[87] D. Tan, K. Huang, S. Yu, and T. Tan, "Efficient night gait recognition based on template matching," in *18th International Conference on Pattern Recognition (ICPR'06)*, vol. 3.   IEEE, 2006, pp. 1000–1003.

[88] S. Zheng, K. Huang, and T. Tan, "Evaluation framework on translation-invariant representation for cumulative foot pressure image," in *2011 18th IEEE International Conference on Image Processing*.   IEEE, 2011, pp. 201–204.

[89] A. Mansur, Y. Makihara, R. Aqmar, and Y. Yagi, "Gait recognition under speed transition," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2014, pp. 2521–2528.

[90] H. Iwama, M. Okumura, Y. Makihara, and Y. Yagi, "The ou-isir gait database comprising the large population dataset and performance evaluation of gait recognition," *IEEE Transactions on Information Forensics and Security*, vol. 7, Issue 5, pp. 1511–1521, Oct. 2012.

[91] T. T. Ngo, Y. Makihara, H. Nagahara, Y. Mukaigawa, and Y. Yagi, "The largest inertial sensor-based gait database and performance evaluation of gait-based personal authentication," *Pattern Recognition*, vol. 47, no. 1, pp. 228 – 237, 2014.

[92] D. S. Matovski, M. S. Nixon, S. Mahmoodi, and J. N. Carter, "The effect of time on gait recognition performance," *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 2, pp. 543–552, 2012.

[93] Y. Makihara, H. Mannami, A. Tsuji, M. Hossain, K. Sugiura, A. Mori, and Y. Yagi, "The ou-isir gait database comprising the treadmill dataset," *IPSJ Trans. on Computer Vision and Applications*, vol. 4, pp. 53–62, Apr. 2012.

[94] D. Cunado, M. S. Nixon, and J. N. Carter, "Using gait as a biometric, via phase-weighted magnitude spectra," in *International Conference on Audio-and Video-Based Biometric Person Authentication*. Springer, 1997, pp. 93–102.

[95] Y. Makihara, D. S. Matovski, M. S. Nixon, J. N. Carter, and Y. Yagi, "Gait recognition: Databases, representations, and applications," *Wiley Encyclopedia of Electrical and Electronics Engineering*, 2015.

[96] S. Samangooei, J. Bustard, M. Nixon, and J. Carter, "On acquisition and analysis of a dataset comprising of gait, ear and semantic data," *Multibiometrics for Human Identification*, p. 277, 2011.

[97] University of South Florida. (2011) Usf gait baseline database. [Online]. Available: http://figment.csee.usf.edu/GaitBaseline/

[98] J. Frank, S. Mannor, and D. Precup, "Data sets: Mobile phone gait recognition data," 2010. [Online]. Available: http://www.cs.mcgill.ca/~jfrank8/data/gait-dataset.html

[99] ——, "Activity recognition with mobile phones," in *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*. Springer, 2011, pp. 630–633.

[100] H. Ng, W.-H. Tan, J. Abdullah, and H.-L. Tong, "Development of vision based multiview gait recognition system with mmugait database," *The Scientific World Journal*, vol. 2014, 2014.

[101] D. Kastaniotis, I. Theodorakopoulos, G. Economou, and S. Fotopoulos, "Gait-based gender recognition using pose information for real time applications," in *18th International Conference on Digital Signal Processing (DSP)*. IEEE, 2013, pp. 1–6.

[102] D. Kastaniotis and University of Patras Computer Vision Group (UPCV). Upcv gait database. [Online]. Available: http://www.upcv.upatras.gr/projects/UPCVgait_dsp/

[103] Y. Ehara, H. Fujimoto, S. Miyazaki, M. Mochimaru, S. Tanaka, and S. Yamamoto, "Comparison of the performance of 3d camera systems ii," *Gait & Posture*, vol. 5, no. 3, pp. 251–255, 1997.

[104] Y. Iwashita, H. Sakano, and R. Kurazume, "Gait recognition robust to speed transition using mutual subspace method," in *International Conference on Image Analysis and Processing*. Springer, 2015, pp. 141–149.